School of Economics and Finance

Three Essays on Bank Liquidity

Chen Zheng

This thesis is presented for the Degree of

Doctor of Philosophy
of
Curtin University

November 2017

Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgment has been made.

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

Signature: ...Chen Zheng...........

Date: 15th November, 2017

Dedication

To my caring parents, Fengying Liu and Shichun Zheng,

AND

To my loving husband, Shu Zhang, and my wonderful daughters, Sara and Susan.

Acknowledgements

Pursuing a PhD is a challenging task and there are many people who have walked alongside me during the last four years of my studies. I am grateful and indebted to all those people who have provided support, assistance and encouragement throughout my PhD journey to make this thesis possible.

First and foremost, I would like to express my deepest gratitude and appreciation to my supervisors, Dr. Tom Cronje and Dr. Adrian Cheung. I thank them for their excellent guidance and continuous support, for their patience and immense knowledge, and for helping me to grow as a researcher. The joy and enthusiasm they have for their research was contagious and motivational for me, even during tough times in the PhD pursuit. This thesis would not be in its present form without their insightful comment and constructive advice. I appreciate all their contributions of time and ideas to make my PhD experience productive, stimulating and enjoyable. I was fortunate to have such excellent supervisors who led me through the whole process. Thanks for supporting and encouraging me through the PhD study.

I would also like to thank the other members of my thesis committee for their helpful discussion and valuable suggestions. My sincere thanks go to Professor Robert Durand, my committee chairman, for his insightful comments and encouragement throughout the entire process. I am also deeply indebted to my former supervisor, Dr. Jason Park, who provided the initial foundation for my thesis by leading me into one of the most exciting areas of banking and introducing me to one of the most challenging econometric software programming. I especially appreciate the critical comment and suggestions from the academic staff in the School of Economics and Finance who helped me identify areas of my research in need of development in my thesis. I would like to thank Dr. Craig Baird who checked my English grammar mistakes and offered suggestions for corrections.

This thesis would not have been possible without the love and encouragement of my family. Words cannot express how grateful I am to my parents for their care and never-ending support in all my pursuits. Special thanks go to my loving husband, Shu

Zhang, who has always been beside me and has supported me in many ways throughout the PhD study. I also thank my wonderful and lovely daughters, Sara Zhang and Susan Zhang, who found their mother always busy. Thank you for your patience, you are my strength.

Also, I gratefully acknowledge the funding sources provided by the Australian Government's Research Training Program (RTP) and the comfortable studying environment offered by Curtin Business School (CBS) so that I could concentrate on my research. Finally, I would like to thank all my friends and particularly fellow PhD candidates at Enterprise Unit 4 Technology Park with whom I have shared a memorable and enjoyable time. You have all contributed in some way to my development as a researcher and academic.

Abstract

One of the main functions of banks is to provide liquidity to the economy. With the massive number of bank failures during the recent financial crisis, the concept of bank liquidity has started to gain increasing attention in banking literature as banks are found to hoard liquidity for self-insurance purposes. However, the holding of the liquidity buffer in the form of cash or risk-free liquid assets is costly because these assets are relatively low-yielding assets. Within this context, this thesis covers three distinct but interrelated empirical studies about bank liquidity. In the first study, the impact of bank capital on the relationship between bank liquidity creation and bank failure risk is explored. The second study determines whether government bailout policy affects the liquidity holdings and liquidity creation of banks, whilst the third study investigates the effect of social capital on bank liquidity holdings.

The thesis consists of five chapters. The first chapter serves as introduction that contains information about why the research was conducted, the structure of the thesis, a summary of the main findings, and it also outlines the contribution of the thesis.

The second chapter "Bank Liquidity Creation, Bank Failure Risk, and Bank Capital", comprises research about the relationship between bank liquidity creation and failure risk, and explores the role of bank capital on the relationship. This chapter shows that conditional on bank capital, an increase in bank liquidity creation decreases bank failure risk. It is consistent with the literature about the liquidity risk sharing function of bank capital that suggests that bank capital absorbs liquidity risk stemming from liquidity creation and thereby reduces the probability of bank failure.

In the third chapter of the thesis "TARP Capital Infusion, Bank Liquidity Holdings and Liquidity Creation", research is conducted about the effects of government bailouts on bank liquidity holdings and bank liquidity creation. Liquidity holdings and liquidity creation are different in that liquidity buffers decrease bank liquidity creation. For example, cash and marketable securities held by a bank decrease liquidity creation since the holding of it restrains the transfer of liquid assets to the public. Findings suggest, within the context of the Troubled Asset Relief Program

(TARP), that government capital bailouts by way of the Capital Purchase Program (CPP), can unlock high levels of inefficient liquid asset holdings by banks. Further analysis also reveals that government intervention through the infusion of capital into banks can decrease the incentives of banks to hold liquidity, which would in turn encourage bank liquidity creation.

The fourth chapter "Social Capital and Bank Liquidity Holdings", entails research about whether county-level social capital, as captured by strength of civic norms and density of social networks, affects the liquidity holdings of banks headquartered in the counties. The findings indicate that banks with headquarters located in counties with higher levels of social capital have lower precautionary demand for liquidity holdings. Further analysis shows that the effect of social capital on liquidity holdings is stronger for small banks; the positive relation between bank liquidity risk and liquidity holdings is less (more) pronounced for banks headquartered in the high (low) social capital counties; and the inverse relation between social capital and bank liquidity holdings is more (less) pronounced for low (high) risk taking banks.

Finally, chapter five concludes the thesis and presents directions for future research.

Refereed Papers, Conference Presentations and Awards

Refereed Papers

1. “Bank Liquidity Creation, Bank Failure Risk, and Bank Capital”, submitted and under review, *Journal of Banking and Finance*

2. “TARP Capital Infusion, Bank Liquidity Holdings and Liquidity Creation”, submitted and under review, *Journal of Financial Services Research*

Conference Presentations

1. The 6th Auckland Finance Meeting, Auckland University of Technology, New Zealand, 2016

2. ECU Business Doctoral and Emerging Scholars Colloquium, Australia, 2016

3. PhD Colloquium at Curtin Business School, Curtin University, Australia, 2016

4. Journal of Contemporary Accounting and Economics Symposium, Taiwan, 2017

5. FMA Asia/Pacific Doctoral Student Consortium (Accepted), Taiwan, 2017

6. PhD Colloquium at Curtin Business School, Curtin University, Australia, 2017

Awards

1. Best Paper Award at the 2016 PhD Colloquium at Curtin Business School, Curtin University, Australia

2. Best Paper Award at the 2016 ECU Business Doctoral and Emerging Scholars Colloquium, Edith Cowan University, Australia

3. Best Paper Award at the 2017 PhD Colloquium at Curtin Business School, Curtin University, Australia

Table of Contents

List of Tables

List of Figures

List of Abbreviations

BCBS	Basel Committee on Banking Supervision
BEA	Bureau of Economic Analysis
CAMELS	Capital adequacy, Asset quality, Management capability, Earnings, Liquidity, and Sensitivity to market risk
CPP	Capital Purchase Program
DID	Difference-In-Difference
FDIC	Federal Deposit Insurance Corporation
IV	Instrument Variables
FED	Federal Reserve System
OLS	Ordinary Least Square
SDI	Statistics on Depository Institutions
SLOOS	Senior Loan Officer Opinion Survey on Bank Lending Practices
TARP	Troubled Asset Relief Program
TBTF	Too-Big-To-Fail
U.S.	United States of America
2SLS	Two-Stage Least Square

CHAPTER 1

INTRODUCTION

1.1 Background and motivation

It is widely recognized that the interbank market serves as an intermediary between banks with liquidity surpluses and banks with liquidity deficits, providing deficit banks with a form of collaborative coinsurance against liquidity shocks (Allen, Carletti and Gale, 2009; Castiglionesi, Feriozzi, LÓRÁNth and Pelizzon, 2014) and surplus banks with higher than risk-free rate of returns. In fact, the interbank market is one of the most liquid funding sources in the financial sector (Heider, Hoerova and Holthausen, 2015) and generally also performs the role of the private lender-of-last-resort for banks' short-term liquidity needs (Acharya and Merrouche, 2012). However, the functioning of the interbank market was severely impaired during the recent financial crisis. In the wake of Lehman's collapse, the interbank market started to become sensitive to borrower characteristics and rationed credit particularly to large banks with high percentages of non-performing loans (Afonso, Kovner and Schoar, 2011). Simultaneously, an increasing number of bank failures occurred. As a result of the drying up of interbank market funding and the increase in solvency risk, banks stopped creating liquidity and started hoarding liquid buffers for self-insurance purposes. Specifically, banks with liquidity surpluses withheld their interbank lending due to uncertainty about the solvency of their counterparties, whilst banks with deficits increased their liquidity holdings to cover themselves against liquidity shocks, such as drawdowns on off-balance sheet commitments and unexpected demand deposit withdrawals (Cornett, McNutt, Strahan and Tehranian, 2011; Ashcraft, McAndrews and Skeie, 2011).

Liquidity creation is risky because it makes banks less liquid (i.e., banks hold illiquid assets and provide liquidity to the public), increases the bank's exposure to the risk that depositors may want to withdraw their money in large numbers at a time when the bank does not have the liquid resources to meet these demands, and raises the likelihood and severity of losses associated with having to dispose of illiquid assets to satisfy the liquidity demands of customers (Allen and Santomero, 1997; Allen and Gale, 2004). Existing literature appears to suggest that there is a positive relationship between liquidity creation and bank failure risk. However, this is a static view without showing the possible channel through which liquidity creation may affect the safety and soundness of individual banks. In addition, it ignores the possibility that banks may change their behaviour endogenously in response to the increased liquidity creation. Other studies indicate that greater liquidity creation should lead to higher levels of capital because banks may strengthen their capital to better assume the losses from selling illiquid assets and to repay the liabilities claimed on demand (Distinguin, Roulet and Tarazi, 2013). Further, most studies indicate that higher capital reduces the probability of bank failure (e.g., Wheelock and Wilson, 2000; Cole and White, 2012). Taken as a whole, the evidence presented here implies that banks that create more liquidity and are then exposed to higher liquidity risk may find it optimal to hold/increase their capital cushion as a precaution against such liquidity shocks. This would, in turn, lower the probability of bank failure. Although numerous studies focused on liquidity creation and failure risk; liquidity creation and bank capital, and bank capital and failure risk, there are still important questions regarding this topic that remain unanswered. For example, the role of bank capital with regard to the relationship between liquidity creation and failure risk has not yet been clarified.[1]

The incentives of banks to hoard liquid assets are driven by two reasons: precautionary motive and strategic motive (Gale and Yorulmazer, 2013). However, a bank's precautionary and strategic demand for liquidity may be excessive relative to its socially efficient level. For example, there is quite strong evidence that the liquidity drying up in the interbank market was triggered by the hoarding behaviour of financial institutions (e.g., Ashcraft, McAndrews and Skeie, 2011; Diamond and Rajan, 2011; Acharya and Skeie, 2011). This would in turn suggest possible policy interventions to address excessive hoarding of liquidity by banks. This is evidenced by the response of the U.S. government to the interbank market disruption and the massive number of

[1] See Section 2.2 in Chapter 2 where the research about determinants of bank failure risk is discussed.

bank failures during the GFC. Rescue tools, such as the Fed's Term Auction Facility and the Treasury's Troubled Asset Relief Program (TARP), were applied to restore the U.S. banking industry. TARP-related literature entails extensive research, but it does not address the impact of the TARP capital injection on the liquidity holdings and levels of liquidity creation of banks that received the bailouts.[2]

Furthermore, banking literature about the determinants of bank liquidity holdings focus on financial and economic factors, but pay little attention on social factors. The concept of social capital gained prominence with the widely cited work of Putnam (1993) and Coleman (1988, 1990). It is best described as the norms and networks that foster cooperation for mutual benefit (Woolcock, 2001). Social capital is an environmental paradigm which captures a region's level of reciprocity, trustworthiness, altruism, solidarity, compassion, and propensity to honor obligations. Through its strong cooperative norm and dense social network channels, social capital in a region can foster an environment that limits managerial opportunistic behaviour (Hasan, Hoi, Wu and Zhang, 2017a). Social capital also facilitates the sharing of information and reduces information asymmetry by decreasing the intensity of moral hazard and adverse selection (Javakhadze, Ferris and French, 2016a). Social capital also offers an alternative mechanism of dispute resolution over contract performance because social rules within social networks stimulate collective actions and impose punishment on divergent and unethical behaviour (e.g., the breach of contract) (Kandori, 1992; McMillan and Woodruff, 2000). Non-financial and/or non-macroeconomic factors such as cultural characteristics like social capital have, based on prior literature, not been considered as possible determinants of bank liquidity holdings.

Motivated by the unanswered questions about bank liquidity, this thesis investigates three distinct but interrelated liquidity research questions namely, the effect of liquidity creation on bank failure risk with consideration of bank capital, the effect of TARP infusion on the liquidity holdings and liquidity creation of banks, and the effect of social capital on the liquidity holdings of banks.

[2] See Section 3.1 in Chapter 3 where the different TARP related research is discussed.

The **first paper** in this thesis proposes a mechanism through which liquidity creation may affect bank failure risk. The primary aim of this paper is to draw attention to the liquidity-risk sharing role that bank capital plays in the relationship between bank liquidity creation and failure risk.

The **second paper** in this thesis postulates that on the one hand, government capital support may provide banks with the assurance of safety and thereby reduce precautionary liquidity hoarding incentives. On the other hand, government capital support may ameliorate the inefficiency by standing ready to inject liquidity to (deficit) banks as this would lower the chance of forced future fire sales of assets by distressed banks and thereby mitigate strategic liquidity hoarding incentives of (surplus) banks. Further, this paper argues that if government capital support can alleviate liquidity hoarding behavior of banks, it may stimulate bank liquidity creation, since liquidity hoarding takes something liquid away from the public and discourages banks from creating liquidity (Berger and Sedunov, 2017). The Troubled Asset Relief Program (TARP), the largest government rescue program in U.S. history, provides a natural testing ground to identify the relationship between government capital support and bank liquidity.

The **third paper** in this thesis attempts to fill the gap in the literature by investigating whether the county-level social capital, as captured by strength of civic norms and density of social networks in a county, affects the liquidity holdings of banks headquartered in the county.

1.2 Structure of thesis and summary of findings

The thesis consists of five chapters including this chapter. The rest of the thesis is structured as follows:

Chapter 2 consists of the first paper "Bank Liquidity Creation, Bank Failure Risk, and Bank Capital" that investigates how bank capital affects the relationship between bank liquidity creation and bank failure risk. According to the modern theory of financial intermediation, liquidity creation is one of the most important roles that banks play in the economy. Liquidity creation is also risky because it exposes banks to the risk of having to dispose of illiquid assets to meet customers' liquidity demands, which in turn can force the bank to prematurely liquidate many of its assets at fire sale prices and to fail. In response to the higher level of illiquidity risk due to liquidity creation, banks may maintain or strengthen their solvency through increased capital to better assume the losses from selling illiquid assets to repay the liabilities claimed on demand and thereby mitigate their default risk.

I find evidence supportive of the liquidity-risk sharing function of bank capital that moderates the relationship between bank liquidity creation and failure risk. Without controlling for bank capital, liquidity creation is positively associated with bank failure risk. However, once bank capital is controlled for, liquidity creation is significantly negative associated with bank failure risk. I also find that the significant negative relationship between bank liquidity creation and bank failure risk is mainly applicable to small banks and the impact of bank capital was more pronounced during the recent financial crisis period.

Chapter 3 presents the second paper "TARP Capital Infusion, Bank Liquidity Holdings and Liquidity Creation" that examines the relationship between government capital support and bank liquidity holdings. Rationales for government bailouts of troubled banks include financial contagion risks, the fear of a systemic meltdown, costly and inefficient liquidity provision by private agents, the risk of a bank run etc. Current literature show that there are two reasons for a bank to hold liquid assets: "precautionary motive" and "strategic motive". The holding of ample amount of liquid assets would help banks become more resilient in periods of financial stress, however, as the recent financial crisis demonstrates, there are also undesirable outcomes that can be associated with liquidity hoarding behaviour of banks. Gale and Yorulmazer (2013) developed a theoretical model of liquidity management to analyse the possibility of liquidity hoarding and its impact on efficiency. They found that the inefficiency of liquidity hoarding caused by incomplete markets always occurs with positive probability in a laisser-faire equilibrium. The central bank, the lender of last resort, can implement a constrained-efficient liquidity allocation to restore efficiency. In particular, if the central bank intervenes very aggressively, it can discourage bankers from holding liquidity. The TARP program provides a natural testing ground to identify the relationship between government bailout and bank liquidity holdings as proposed by Gale and Yorulmazer (2013).

The findings are supportive of the empirical dominance of the “precautionary motive” and “strategic motive” of liquidity holdings in the banking literature. As such, the findings provide strong evidence that higher government capital support (TARP) can be associated with lower level of liquidity holdings. Further analysis reveals that by unlocking high levels of liquid asset holdings by banks, the TARP program achieved the stated policy objective of increasing bank liquidity creation.

Chapter 4 presents the third paper “Social Capital and Bank Liquidity Holdings” that investigates whether the county-level social capital, as captured by strength of civic norms and density of social networks in a county, affects the liquidity holdings of banks headquartered in the counties. Social capital may reduce liquidity risk and ease external financing constraints through its effect on trust, contract enforcement and information asymmetry. Moreover, through its strong cooperative norm and dense social network channels, social capital in a county can foster an environment that limits managerial opportunistic behavior. For example, the social norms of high social capital regions induce managers to behave more honestly and restrain managers by disciplining their opportunistic behavior (e.g., excessive risk taking and risk shifting); and the dense networks in high social capital regions increase the reputational costs of opportunistic behavior and encourage consistent trustworthy and reliable behavior from managers.

I find that banks with headquarters located in counties with higher levels of social capital have lower precautionary demand for liquidity holdings. Further analysis shows that the effect of social capital on liquidity holdings is stronger for small banks. I also find that the relation between bank liquidity risk and liquidity holdings is less (more) pronounced for banks headquartered in the high (low) social capital counties. Moreover, the result indicates that the inverse relation between social capital and bank liquidity holdings is more (less) pronounced for low (high) risk taking banks. These results suggest that social capital plays an important role in reducing inefficiently high levels of liquidity holdings by banks.

Chapter 5 provides a summary of major findings from the empirical analysis in this thesis. The chapter also presents overall conclusions and policy implications. In addition, it discusses directions for future research.

Table 1.1 Summary of the Findings

Chapter	Hypothesis	Findings
Two	H: Given bank capital, bank liquidity creation is negatively associated with bank failure risk.	Strong support
Three	H: Higher government capital support is associated with lower levels of liquidity holdings by banks. H1: Higher government capital support is associated with higher levels of bank liquidity creation.	Strong support
Four	H: Banks headquartered in low (high) social capital counties hold high (low) levels of liquidity. H1: The positive relation between bank liquidity risk and liquidity holdings is less (more) pronounced for banks headquartered in high (low) social capital counties. H2: The inverse relation between social capital and bank liquidity holdings is stronger for small banks than large banks H3: The inverse relation between social capital and bank liquidity holdings is more (less) pronounced for low (high) risk taking banks	Strong support

1.3 Contribution to the literature

This study takes bank liquidity research one step further by shedding light on three distinct but interrelated topics that are centered on bank liquidity, i.e., bank failure risk, government bailout and social capital, which have largely been unexplored in the banking literature. The findings of the thesis contribute to the literature in the following ways:

Chapter 2 of the thesis contributes significantly in two ways to the existing research. Firstly, although the existing body of research has clearly established a connection between liquidity creation and bank capital (e.g., Berger and Bouwman, 2009; Distinguin, Roulet and Tarazi, 2013), and between bank capital and failure risk (e.g., Berger and Bouwman, 2013), little research to date has empirically analysed the role played by bank capital in moderating the relationship between bank liquidity creation and bank failures. This study sheds new light on the liquidity risk-sharing function of bank capital. As discussed in this paper, it is important to consider the endogenous reaction of banks (e.g., banks may actively adjust their capital ratio) towards a higher liquidity risk stemming from liquidity creation. This is the gap this paper wants to fill to the existing literature. Secondly, this study offers important policy implications for policymakers and bank regulators. Prudential regulation, in the form of liquidity or capital requirements, is designed to enhance the resilience to shocks of the banking system by requiring institutions to maintain prudent levels of liquidity and capital under a broad range of market conditions. New liquidity and capital requirements have been proposed under Basel III. There remain, however, some outstanding issues and details. Among these, the link between capital and liquidity requirements has, perhaps, prompted most debate in the literature. The results in this paper suggest that capital and liquidity requirements cannot be isolated. Specifically, the policymakers should consider the liquidity-risk sharing function of bank capital in the liquidity management of banks and evaluate its effect on the relationship between liquidity creation and bank failure risk. Further, the results clearly show that one size does not fit all when it comes to capital and liquidity regulation. Presumably, large banks might underestimate liquidity risk and maintain low capital ratios because of their too-big-to-fail position. The findings indicate that stringent capital requirements should be imposed on large banks to induce them to raise capital and reduce the probability of failure.

Chapter 3 of this thesis extends the government bailout literature by empirically investigating the effects of the TARP capital infusion on bank liquidity holdings and liquidity creation. Government bailout has received considerable attention in the wake of the economic crisis and the design of the government intervention policy has prompted an interesting debate among regulators, supervisors, academics and practitioners. The primary contribution of this paper to the existing literature is that it provides additional evaluation of the effectiveness of the TARP program, and will be of particular importance to policymakers for assessing and designing government-supported schemes. The TARP-related literature entail extensive research, but do not address the impact of the TARP capital injection on bank liquidity. This paper bridges this gap in the literature. As noted in this paper, banks' precautionary and strategic demand for liquidity may be excessive relative to its socially efficient level (e.g., during the recent financial crisis 2007-2009). This suggests possible policy interventions to address excessive hoarding of liquidity by banks. This study offers important policy implications for policymakers and bank regulators as it suggests that government capital support (e.g., TARP recapitalization) may reduce liquidity hoarding behavior of banks. For example, government capital support may provide banks with the assurance of safety and thereby reduce precautionary liquidity hoarding incentives. Government capital support may also reduce this inefficiency by injecting liquidity to (deficit) banks and thereby mitigate strategic liquidity hoarding incentives of (surplus) banks. Further, if government intervention through the infusion of capital into banks can decrease banks' incentives to hold liquidity, then bailout policy will be effective in stimulating bank lending and/or liquidity creation and assisting economic recovery, which is of particular interest to policymakers and bank managers. This paper expands upon the bank lending channel literature by broadening the focus to bank liquidity creation – which includes much more than lending, as bank lending is only one component of asset-side liquidity creation. It is important to study liquidity creation because, according to the modern theory of financial intermediation, liquidity creation is a core function of banks to support the macro-economy. Perhaps more importantly, liquidity creation is viewed as the best available measure of total bank output.

The contribution of ***Chapter 4*** is threefold. Firstly, this study contributes to a more comprehensive understanding of the determinants of bank liquidity holdings. Missing from the literature is the idea that non-financial and/or non-macroeconomic factors such as cultural characteristics like social capital might also influence the bank's liquidity holdings. This study makes a contribution to the literature by proposing social capital as a new determinant of bank liquidity holdings. Secondly, the findings of this paper have important implications for banking regulation under Basel III initiatives. It is well-known that liquidity risk led to the hoarding of liquid assets and widespread bank failures during the recent financial crisis (Radde, 2015; DeYoung and Jang, 2016). In response to this, the Basel Committee on Banking Supervision (BCBS) has proposed the Basel III Accord in 2010. It requires banks to alter their balance sheets to comply with two new liquidity regulations: the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR). The evidence in this study indicates that bank supervisors and regulators should not only actively monitor the balance sheets of banks, but also pay special attention to the social capital in the counties where banks are headquartered since social capital affects bank liquidity holdings. This supports the introduction of other criteria to complement the traditional, micro-prudential banking regulation approach. Thirdly, this study contributes to the emerging literature on the effects of social capital on corporate decision-making and behaviour (Javakhadze, Ferris and French, 2016a; Hasan, Hoi, Wu and Zhang, 2017a). In this regard, the results of this research indicate that social capital may provide banks with assurance of safety, which in turn reduces inefficiently high levels of precautionary liquidity holdings by banks. The findings also serve as indication that the social environment, in the context of norms and networks surrounding bank headquarters, limit the opportunistic behaviour (e.g., excessive risk taking) of bank management, which in turn alleviates the precautionary motives of banks for holding liquidity.

CHAPTER 2

BANK LIQUIDITY CREATION, BANK FAILURE RISK, AND BANK CAPITAL

2.1 Introduction

A large number of bank failures occurred during the recent financial crisis.[3] Although numerous studies attempted to predict bank failures (e.g., Cole and Gunther, 1998; Jin, Kanagaretnam and Lobo, 2011; Cleary and Hebb, 2016), many important questions regarding this topic still remain unanswered. For example, the role of bank liquidity creation on bank failure is not clearly addressed in the literature. According to the modern theory of financial intermediation, one of the major roles performed by banks is liquidity creation. Banks create liquidity on the balance sheet by activities, such as transforming illiquid assets into liquid liabilities (e.g., Bryant, 1980; Diamond and Dybvig, 1983). Banks also create liquidity by way of off-balance sheet activities, such as providing standby letters of credit and loan commitments to their customers (e.g., Holmström and Tirole, 1998; Kashyap, Rajan and Stein, 2002; Thakor, 2005).[4]

With respect to the effect of liquidity creation on bank failure risk, one line of argument, put forward by Diamond and Dybvig (1983), and extended by Allen and Santomero (1997) and Allen and Gale (2004), accentuates that liquidity creation exposes banks to the risk of having to dispose of illiquid assets to meet customers'

[3] FDIC reported that it closed 140, 157 and 92 financial institutions in 2009, 2010 and 2011, respectively. For example, Lehman Brothers collapsed in mid-September 2008; Wachovia agreed to merge with Well Fargo in October 2008; Washington Mutual became the largest U.S. bank ever to fail, with most of its assets and liabilities purchased from the FDIC by J.P. Morgan Chase in September 2008; and Bank of America completed the acquisition of Merrill Lynch in January 2009.

[4] Note that liquidity buffers decrease bank liquidity creation. For example, cash and marketable securities held by a bank decrease liquidity creation since the holding of it restrains the transfer of liquid assets to the public (Berger and Sedunov, 2017). Another difference between liquidity holding and liquidity creation is that the former reduces the liquidity risk of banks while the latter exposes banks to liquidity risk.

liquidity demands.[5] For example, sudden and large withdrawals from demand depositors and borrowers with credit line facilities can force the bank to prematurely liquidate many of its assets at fire sale prices and to fail (Diamond and Rajan, 2011). This set of theories predicts that liquidity creation leaves banks vulnerable to insolvency – the more the liquidity creation, the greater the likelihood of bank failure. However, this is a static view without taking into consideration that banks may adopt ways to address the presence of increased risk stemming from liquidity creation. Specifically, banks may strengthen or build up their capital buffers in response to the perceived risk exposure (Castiglionesi, Feriozzi, LÓRÁNth and Pelizzon, 2014). Bank capital is important since it implicates the survival probability of banks in two ways. Firstly, higher bank capital increases the buffers of banks against shocks to asset values (e.g., Repullo, 2004; Von Thadden, 2004). Secondly, according to incentive-based theories, higher bank capital strengthens the incentive of banks to monitor their relationships with borrowers (e.g., Holmström and Tirole, 1998) or reduces the excessive risk taking incentives of banks (Acharya, Mehran and Thakor, 2016). These incentive-based theories collectively imply that liquidity creation, acknowledged as a risk in existing literature, can be negatively associated with bank failure due to the tendency of banks to adopt ways, with specific reference to the increase in capital, to manage/mitigate the risk.

Using a dataset of all U.S. financial institutions that were insured by Federal Deposit Insurance Corporation (FDIC) over the period of 2003:Q1 to 2014:Q4 with 297,610 bank-quarter observations, I examine whether and how bank liquidity creation influences bank failure. I have two major findings. First, liquidity creation is negatively associated with bank failure risk. This is because banks that create more liquidity and are then exposed to higher liquidity risk in general accumulate more capital as a precaution against illiquidity risk from bank liquidity creation. The higher capital, consequently lowers the probability of bank failure. This finding supports the findings of Castiglionesi, Feriozzi, LÓRÁNth and Pelizzon (2014) that banks may use capital to deal with undiversifiable liquidity risk that cannot be diversified away by interbank markets. The second main finding is that the negative and significant

[5] The maturity mismatch like when banks take short term deposits from lenders and make longer term investments, is inherent in liquidity creation and exposes banks to a variety of risks, including liquidity risk, credit risk and interest rate risk (Bouwman, 2013)

relationship between bank liquidity creation and bank failure risk is mainly applicable to smaller banks and the impact of bank capital on the relationship between liquidity creation and bank failure risk is more pronounced during the recent financial crisis period.

This paper contributes to the current literature by providing significant findings about the impact of the liquidity-risk sharing role of bank capital in moderating the relationship between bank liquidity creation and bank failures. To the best of my knowledge, this aspect has not been addressed by other research papers. Furthermore, policy considerations motivate this research. With respect to prudential regulation, Basel III is designed to make individual banks more resilient to common and idiosyncratic shocks by requiring financial institutions to maintain prudent levels of liquidity and capital buffers. Therefore, understanding the links between liquidity creation, bank capital and bank failure is important, especially for policymakers and bank boards. Currently, researchers have not determined how the interaction between liquidity creation and bank capital affects the failure risk of individual banks. This paper fills this gap.

This paper is closely related to the paper of Imbierowicz and Rauch (2014) that examines the effect of the interaction between liquidity risk and credit risk on the probability of bank default (PD). They used the Berger and Bouwman's (2009) preferred liquidity creation measure (hereafter referred to as BB measure) as a proxy for liquidity risk in their robustness checks. They found that the effect of the interaction depends on the overall level of bank risk and can either aggravate or mitigate the PD. This paper is also related to the paper of Fungáčová, Turk and Weill (2015). They found that high liquidity creation significantly increases the probability of bank failure of Russian banks. However, they also admitted that banks with very low liquidity creation ratios are inclined to fail. Their explanation is that liquidity creation is one of the most important roles that banks perform in the economy and that it is a proxy for overall bank output. Therefore, the inability to perform this function likely signals trouble. The findings of my paper support this view. Specifically, I find that banks that create less liquidity are more likely to fail since they seem to have too low levels of capital buffers to even absorb the liquidity risk from their lower liquidity creation activities. My paper differs from these two papers in three respects. Firstly, they do not distinguish between diversifiable and undiversifiable liquidity risk stemming from bank liquidity creation. My paper does since Hong, Huang and Wu (2014) found that undiversifiable liquidity risk (rather than diversifiable liquidity risk) is a major contributor to bank failure. Secondly, my paper considers the liquidity risk-sharing function of bank capital in moderating the relationship between liquidity creation and bank failure risk. As noted previously, it is important to consider the endogenous reaction of banks towards higher liquidity risk stemming from liquidity creation. Thirdly, since Berger and Bouwman (2009) found that liquidity creation differs substantially between different bank sizes. My paper addresses this aspect by examining how bank capital affects the relationship between liquidity creation and bank failure across different bank size categories. The findings show that the negative and significant effect of liquidity creation on bank failure is most prominent for small banks. This paper is most closely related to DeYoung, Distinguin and Tarazi's (2018) paper which finds that banks adjust their liquidity ratios upward in response to negative shocks to their capital ratios. My research complements their paper by showing that banks may also increase their capital ratios in response to liquidity shock/risk stemming from liquidity creation. The findings of both studies suggest that there is an interrelationship between bank capital and bank liquidity.

The remainder of this paper is organized as follows. Section 2.2 provides literature review and develops testable hypothesis. Section 2.3 focuses on sample, variables, and econometric model. Section 2.4 presents the empirical results of this study, followed by the additional analysis in Section 2.5 where bank capital channel is discussed. A series of related robustness checks are conducted in Section 2.6, followed by the conclusion in Section 2.7.

2.2 Related literature and hypothesis development

2.2.1 Literature review

In this section, I discuss two strands of literature to substantiate research gaps in terms of the purpose of this paper: the relationship between bank capital and liquidity creation and the determinants of bank failure.

According to Berger and Bouwman (2009), bank capital may affect the ability of banks to create liquidity in two opposing ways. According to the "financial fragility-crowding out" hypothesis, capital has a negative effect on liquidity creation because a deposit contract would mitigate the hold-up problem of banks that cannot be resolved by bank capital (Diamond and Rajan, 2000, 2001) and a higher capital ratio may reduce liquidity creation through the crowding out of deposits (Gorton and Winton, 2017). In contrast, the "risk absorption" hypothesis, implies that there is a positive effect of capital on liquidity creation because capital helps to absorb the illiquidity risks associated with liquidity creation and expands the risk-bearing capacity of banks (e.g., Bhattacharya and Thakor, 1993; Allen and Santomero, 1997; Allen and Gale, 2004; Repullo, 2004; Von Thadden, 2004; Coval and Thakor, 2005). Berger and Bouwman (2009) researched the relationship between bank capital and liquidity creation using a sample of U.S. commercial banks from 1993 to 2003 and found empirical support for both hypotheses. For large banks, which create by far most of the liquidity, they found a positive relationship (driven largely by the effect on off-balance sheet activities), consistent with the "risk absorption" effect, whereas for small banks, the relationship is negative, consistent with the "financial fragility-crowding out" effect. Building on the "risk absorption" hypothesis and extending the paper of Berger and Bouwman (2009), I propose a mechanism through which the relation moves from liquidity creation to bank capital.[6] More specifically, liquidity creation is risky, i.e., banks tend to suffer losses if they must quickly dispose of illiquid assets to meet the demands of those holding liquid liabilities (e.g., Allen and Santomero, 1997; Allen and Gale, 2004). In response to the higher level of illiquidity risk due to liquidity creation, banks

[6] Expanding upon Berger and Bouwman (2009), emerging literature examines the effect of liquidity creation on bank capital (e.g., Tran, Lin and Nguyen, 2016; Horváth, Seidler and Weill, 2014; Distinguin, Roulet and Tarazi, 2013; Fu, Lin and Molyneux, 2016).

may maintain or strengthen their solvency through increased capital to enable them to mitigate their default risk when they assume the losses from selling illiquid assets to repay the liabilities claimed on demand.[7]

Turning to the empirical literature about the determinants of bank failure, there is a broad body of research testing the influence of a wide variety of bank accounting variables (e.g., CAMELS ratings[8]), local market condition variables and general economic factors on bank failure. Papers that precede the recent financial crisis such as that of Cole and Gunther (1995, 1998) and Wheelock and Wilson (2000) found that bank failure risk is mainly driven by low capitalization, low earnings and other measures of poor performance. Recent papers explored the determinants of bank failures during the recent financial crisis (e.g., Cole and White, 2012; Aubuchon and Wheelock, 2010; Berger and Bouwman, 2013; DeYoung and Torna, 2013; Ng and Roychowdhury, 2014; Berger, Imbierowicz and Rauch, 2016). Cole and White (2012) focused on the impact of CAMELS-based accounting variables on bank failure risk. They found that banks with more capital, better asset quality, higher earnings and more liquidity were less likely to fail during 2009-2010. Aubuchon and Wheelock (2010) compared bank failures in the U.S. during two periods of time: from 1987 to 1992 and from 2007 to 2010. They analysed the influence of local macroeconomic factors on the probability of bank default. Their study shows that for both periods, bank failures were more likely to occur in states experiencing more severe economic distress. Berger

[7] While it is beyond the scope of this study, it is important to note that since the pioneering work of Berger and Bouwman (2009), a handful of recent papers follow their study and/or use their liquidity creation measures to investigate different issues. For example, prior literature shows that increased bank competition reduces liquidity creation (Horváth, Seidler and Weill, 2016; Jiang, Levine and Lin, 2016); capital support does not affect liquidity creation (Berger, Bouwman, Kick and Schaeck, 2016); deposit insurance reduces the impact of capital on liquidity creation for Russian banks that are most affected by the introduction of deposit insurance program (Fungáčová, Weill and Zhou, 2017); there is a positive impact of the bank merger activity on liquidity creation (Pana, Park and Query, 2010; Baltas, Kapetanios, Tsionas and Izzeldin, 2017); internal bank governance has a positive effect on liquidity creation (Díaz and Huang, 2017); higher ability managers create more liquidity and take more risk, however, they reduce liquidity creation as a way to de-leverage their balance sheets during times of financial crisis (Andreou, Philip and Robejsek, 2016); higher asset market liquidity leads to more bank liquidity creation (Chatterjee, 2015); monetary policy has a more pronounced effect on liquidity creation of small banks than that of large banks (Chatterjee, 2015; Berger and Bouwman, 2017); liquidity creation is positively and significantly related to economic growth (Berger and Sedunov, 2017; Fidrmuc, Fungáčová and Weill, 2015); regulatory capital and liquidity creation affect each other positively after controlling for bank profitability, and banks which create more liquidity and exhibit higher illiquidity risk have lower profitability (Tran, Lin and Nguyen, 2016).

[8] CAMELS is an acronym for Capital adequacy, Asset quality, Management, Earnings, Liquidity and Sensitivity to market risk.

and Bouwman (2013) investigated the effects of equity capital on bank survival during periods of banking crises, market crises, and normal times. They found that capital helps small banks to increase their probability of survival at all times and it enhances the survival of medium and large banks largely during banking crises periods. DeYoung and Torna (2013) focused on the impact of non-traditional banking activities on the probability of bank failure during the period of 2008-2010. Their findings show that different sources of non-interest income have different effects on bank failure. Ng and Roychowdhury (2014) found that "add-backs" of loan loss reserves to regulatory capital were positively associated with bank failure risk during the recent economic crisis. Berger, Imbierowicz and Rauch (2016) analysed the roles of corporate governance in bank failures during the recent financial crisis. They found that the ownership structure of a bank is an important predictor of bank failure. The impact of bank liquidity creation on bank failure is still unclear in the literature, although previous studies attempted to predict bank failures. According to the modern theory of financial intermediation, liquidity creation is a core function of banks to support the macro-economy. Perhaps more importantly, liquidity creation is viewed as the best available measure of total bank output (Berger and Sedunov, 2017). It is therefore important to research the liquidity creation and bank failure relationship further.

On the whole, although existing research has clearly established a connection between liquidity creation and bank capital (e.g., Berger and Bouwman, 2009; Distinguin, Roulet and Tarazi, 2013), and between bank capital and failure risk (e.g., Berger and Bouwman, 2013), little research to date has empirically analysed the impact of bank capital and changes in bank capital on the relationship between bank liquidity creation on bank failures.

2.2.2 Hypothesis development

Liquidity creation is risky because it makes banks less liquid (i.e., banks hold illiquid assets when they provide liquidity to the external entities), increases the bank's exposure to risk, and raises the likelihood and severity of losses associated with having to dispose of illiquid assets to satisfy the liquidity demands of customers (Allen and

Santomero, 1997; Allen and Gale, 2004). In extreme situations, aggregate increases in liquidity demand can result in bank runs by depositors (Diamond and Dybvig, 1983).

The recent financial crisis demonstrated explicitly that illiquidity can be considered a main source of banking fragility. A number of papers have examined the relationship between bank liquidity creation and the stability of the banking system as a whole. For example, Acharya and Naqvi (2012) developed a theoretical model showing that when the macroeconomic risk is high, “flight to quality” leaves banks with ample liquidity, which induces banks to relax lending standards and this situation gives rise to excessive lending that may cause asset bubbles and financial crises. Thakor (2005) provided a theoretical argument that the reputational concerns of banks lead to greater liquidity creation by way of loan commitments during economic booms. He also stated that the banking sector will suffer a decline in stability following the economic boom due to the higher defaults by bank borrowers. On the empirical side, Dell’ariccia, Igan and Laeven (2012) found that a relaxation of lending standards and the abundant availability of liquidity during the credit boom of 2000-2006 may have contributed to the financial instability of the banking system. Berger and Bouwman (2017) found that the banking crises in the U.S. have been preceded by periods of abnormal liquidity creation. Collectively, these papers indicate that increased liquidity creation may lead to the higher probability of banking instability.

However, this is a static view not addressing the possible channel through which liquidity creation may affect the safety and soundness of individual banks differently. In addition, it is of extreme importance to identify actions that could be applied by banks to reduce their failure risk amidst liquidity creation. For example, banks may strengthen their capital buffer so as to mitigate their default risk stemming from liquidity creation. This paper builds on and extends the existing literature by empirically investigating the impact of bank capital on the relationship between bank liquidity creation and bank failures because existing research show that both idiosyncratic and systemic liquidity risks exist and that banks may require capital buffers to hedge their systematic liquidity risks that may contribute significantly to bank failures (Hong, Huang and Wu, 2014; Castiglionesi, Feriozzi, LÓRÁNth and Pelizzon, 2014). Further, most studies indicate that higher capital buffers can curb banks' risk-taking behaviour (e.g., Khan, Scheule and Wu, 2017) and reduce the probability of bank failure (e.g., Wheelock and Wilson, 2000; Cole and White, 2012). Taken as a whole, it is expected that banks that create more liquidity and are then exposed to higher (undiversifiable) liquidity risk may find it optimal to hold/increase their capital levels to absorb such liquidity shocks. This would, in turn, lower the probability of bank failure.

Based on the preceding literature review and discussion, my hypothesis for the relationship between bank liquidity creation and bank failure risk is:

Given bank capital, bank liquidity creation is negatively associated with bank failure risk.

2.3 Sample, variables, and econometric model

2.3.1 Sample and data

The sample of banks in this paper consists of all U.S. institutions that were insured by the Federal Deposit Insurance Corporation (FDIC) over the period from 2003:Q1 to 2014:Q4 with 297,610 bank-quarter observations. The 2003 to 2014 time period is unique in that it contains data before, during and after the largest financial crisis in recent history. It starts five years before the GFC and ends five years after the GFC to allow for the long-term effect of this exogenous shock on the relation between bank liquidity creation and failure risk. The data is obtained from several sources. Quarterly financial data is sourced from the Statistics on Depository Institution (SDI) reports of the FDIC bank data and statistics.[9] Bank failure information is obtained from the FDIC's failed banks list.[10] In fact, before 2008 very few or no failures occurred for a number of years (Figure 2.1), but the massive number of bank failures during the recent financial crisis offers a valuable opportunity for me to study the effect of bank

[9] https://www5.fdic.gov/sdi/download_large_list_outside.asp
[10] https://www.fdic.gov/bank/individual/failed/banklist.html

liquidity creation on bank failure. This study makes use of the publicly available dataset of quarterly bank liquidity creation for U.S. commercial banks over the observation period that was compiled by Allen N. Berger and Christa Bouwman.[11] Macroeconomic data, such as GDP, Federal funds rate, yield spread and gross private savings are taken from the St. Louis Federal Reserve "FRED" public database. Local market economic and demographic data are sourced from the Bureau of Economic Analysis (BEA) (e.g., per capita personal income, total employment and population) and Fed website (e.g., Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS)).[12] All the aforementioned data sources are merged together to construct the dataset for this study.

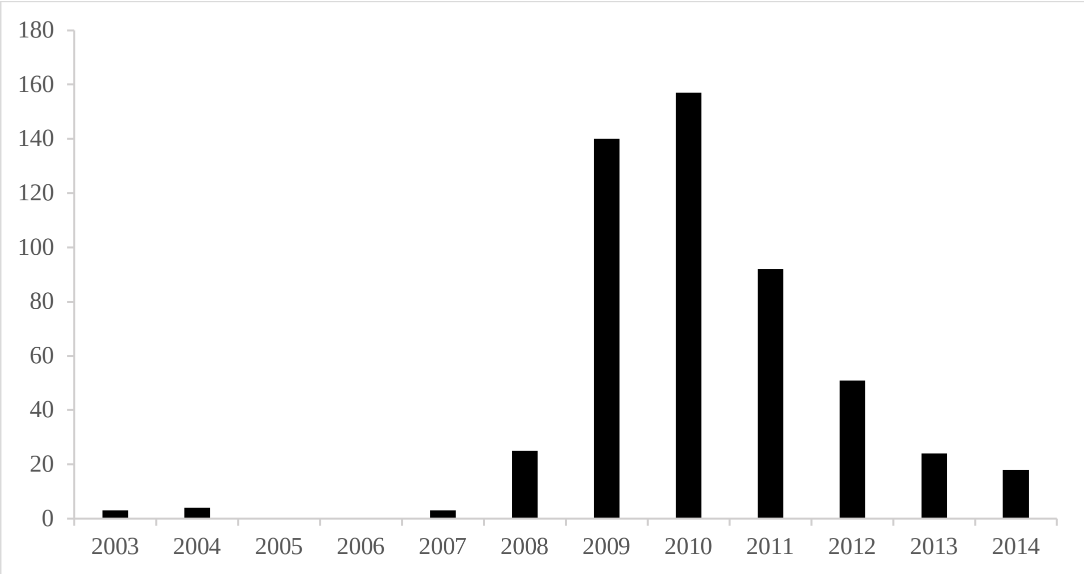

Figure 2.1 Number of bank failures in the U.S. between 2003 and 2014. Source: Federal Deposit Insurance Corporation (FDIC)

2.3.2 Dependent and main independent variables

The relationship between bank liquidity creation and bank failure risk is the main focus area of this study. Therefore bank failure risk serves as the dependent variable and bank liquidity creation as the main independent variable. To analyse such

[11] I am grateful to Christa Bouwman for providing the bank liquidity creation data. It is downloadable from Christa Bouwman's personal website (https://sites.google.com/a/tamu.edu/bouwman/data).
[12] https://www.federalreserve.gov/boarddocs/SnLoanSurvey/default.htm

relationship, a binary performance variable (*bf*) is used to indicate whether a bank fails within the next 12 months after a specific financial report date. If failure occurs, it is flagged as "bad" and is assigned the binary value of one. Otherwise, it is flagged as "good" and is assigned the binary value of zero.

For the bank liquidity creation variable, I use the measure proposed in the ground-breaking work of Berger and Bouwman (2009). BB measure is a comprehensive single measure of bank liquidity creation that considers all the bank's on-balance sheet and off-balance sheet activities. To summarize briefly, BB measure is the weighted sum of all assets, liabilities, equity, and off-balance sheet activities. Since liquidity is created when banks transform illiquid assets into liquid liabilities, positive weights are given to both illiquid assets and liquid liabilities. Similarly, since banks destroy liquidity when they transform liquid assets into illiquid liabilities or equity, negative weights are given to liquid assets, illiquid liabilities, and equity. Off-balance sheet activities are assigned weights consistent with those assigned to functionally similar on-balance sheet activities. Berger and Bouwman (2009) compute four measures of liquidity. The first two are based on loan categories (*cat*) with inclusion (*fat*) or exclusion (*nonfat*) of off-balance sheet activities. The third and fourth measures are based on maturities (mat) with the inclusion (*fat*) or exclusion (*nonfat*) of off-balance sheet activities. They argue that the two liquidity measures based on category (*catfat* and *catnonfat*) are preferred to the liquidity measures based on maturity (*matfat* and *matnonfat*) because they are better indicators of the ease, cost and time for banks to dispose of their obligations to obtain liquid funds. Therefore, in my study, I use two of BB measures: *catfat* and *catnonfat: catfat* is the sum of on-balance sheet liquidity and off-balance sheet liquidity and *catnonfat* measures liquidity created on the balance sheet. Both measures are standardized by gross total assets.[13] A detailed description of the liquidity level of bank activities is provided in Appendix 2.1. The *catfat* and *catnonfat* measures are calculated as follows:

[13] Gross total assets include total assets plus allowance for loan and lease losses and the allocated risk reserve.

$$catfat = 0.5 \times (\text{illiquid assets } + \text{liquid liabilities } + \text{illiquid guarantees}) + 0 \times (\text{semiliquid assets } + \text{semiliquid liabilities } + \text{semiliquid guarantees}) - 0.5 \times (\text{liquid assets } + \text{illiquid liabilities } + \text{equity} + \text{liquid guarantees} + \text{liquid derivatives}) \quad (1)$$

$$catnonfat = 0.5 \times (\text{illiquid assets } + \text{ liquid liabilities}) + 0 \times (\text{semiliquid assets } + \text{ semiliquid liabilities}) - 0.5 \times (\text{liquid assets } + \text{ illiquid liabilities } + \text{ equity}) \quad (2)$$

Figure 2.2 and 2.3 graphically presents *catfat* and *catnonfat* data for the sample period. Figure 2.2 shows that on-balance sheet liquidity creation increased steadily during the sample period whilst aggregate liquidity creation including both on- and off-balance sheet activities plummeted in 2008Q3 and grew gradually since 2010Q1. Figure 2.3 shows a similar pattern to Figure 2.2. For example, the mean and median value of liquidity creation dropped significantly in 2008Q3. This is not surprising given that following the Lehman failure on September 15, 2008, a significant, but relatively mild, financial disruption was transformed into a full-fledged financial crisis that led to a large increase in uncertainty and a wave of distressed selling of securities that caused a collapse in asset prices. However, with the implementation of conventional and unconventional monetary policies, and bailouts of some banks and financial institutions by the U.S. Federal Reserve and Treasury, financial markets began to recover in 2010.

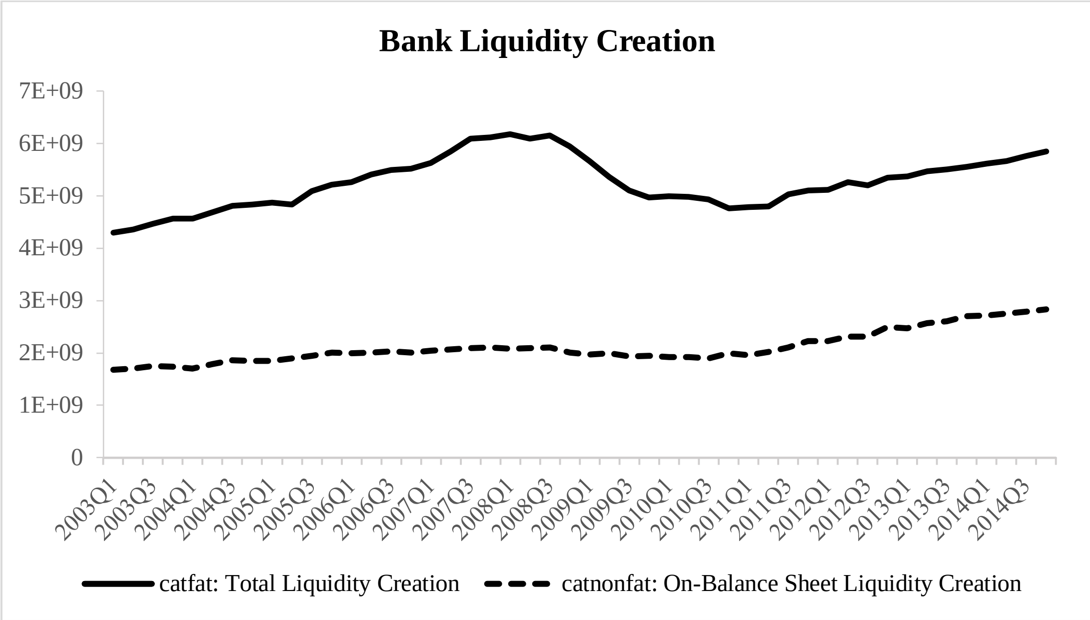

Figure 2.2 Bank liquidity creation. This figure plots bank liquidity creation data (in US$ thousand) for the U.S. banks. The variables are *catfat*: bank aggregate liquidity creation measure that includes both on- and off-balance sheet activities, *catnonfat*: bank liquidity creation measure that includes banks' on-balance sheet activities. The variables are described in details in Berger and Bouwman (2009). Sample: Quarterly data from 2003 to 2014.

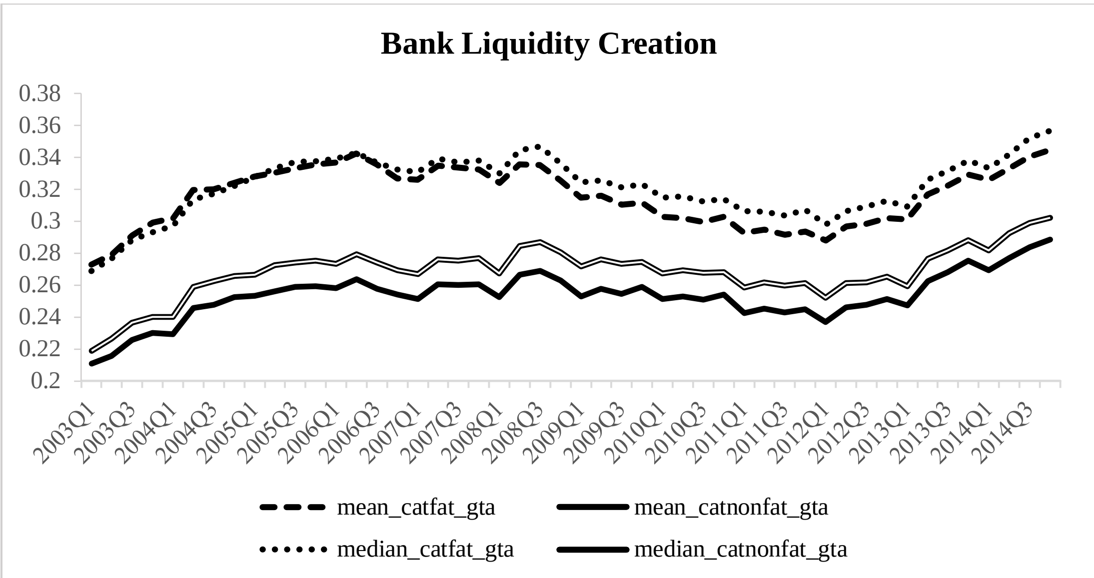

Figure 2.3 Bank liquidity creation. This figure plots mean and median value of dollar amount of bank liquidity creation normalized by gross total assets (GTA) for the U.S. banks. The variables are *catfat*: bank aggregate liquidity creation measure that includes both on- and off-balance sheet activities, *catnonfat*: bank liquidity creation measure that includes banks' on-balance sheet activities. The variables are described in details in Berger and Bouwman (2009). Sample: Quarterly data from 2003 to 2014.

2.3.3 Control variables

In this study, a wide range of bank-specific characteristics, macroeconomic variables, and local market variables are employed as control variables. Bank-specific characteristics may have significant relationships with bank performance in terms of success or failure and are selected from empirical bank failure-predicting models. The macroeconomic variables are used to control for macroeconomic influences (e.g., monetary policy). The local market variables are used to proxy loan demand that varies across banks and regions, as well as county-level economic and demographic conditions.

2.3.3.1 Bank-specific characteristics

A very recent and still developing body of literature indicates the possibility that in addition to bank capital, the relationship between liquidity creation and bank failure might potentially be affected by precautionary liquidity hoarding and stable liabilities.

Precautionary liquidity hoarding is the bank's rational response to potential liquidity risk and one of the striking features of the recent financial crisis (e.g., Berrospide, 2013; Cornett, McNutt, Strahan and Tehranian, 2011; Ashcraft, McAndrews and Skeie, 2011). Banks may hold a sufficiently ample amount of liquid assets as self-insurance against the occurrence of a liquidity shock. However, liquidity hoarding may aggravate liquidity/failure risk. Firstly, interbank market freezes may occur when the liquidity accumulated by banks as a precaution against liquidity shocks dries up (Allen, Carletti and Gale, 2009; Acharya and Skeie, 2011). The interbank market breakdown makes it almost impossible to reallocate liquidity from banks with liquidity surpluses to banks with liquidity shortages and to diversify idiosyncratic liquidity risk away. Secondly, liquidity hoarding can also lead to market illiquidity at the aggregate level. Gârleanu and Pedersen (2007) pointed out that if this negative externality effect outweighs the beneficial liquidity buffer effect, then a positive relationship between liquidity buffer and bank failure may exist.

One may also argue that banks can substitute stable liabilities for bank capital as a risk-sharing mechanism due to the fact that with implicit and explicit government support of banks, deposits can be viewed as a natural hedge against liquidity risk exposure (Gatev and Strahan, 2006; Gatev, Schuermann and Strahan, 2009). Kashyap, Rajan and Stein (2002) argue that as long as the liquidity needs of borrowers and depositors are not perfectly correlated, banks can *ex ante* enjoy a risk-reducing synergy by combining transaction deposits with unused loan commitments. However, banks may experience *ex post* a coincident liquidity demand from depositors and borrowers leading to a more fragile financial system (Acharya and Mora, 2015). Furthermore, bank deposits may be viewed as risky during a bank-centered crisis (e.g., U.S. subprime crisis), despite deposit insurance. At the onset of the U.S subprime crisis, there was collective withdrawal from deposit accounts with funding inflow into government sponsored or issued securities, as investors were concerned about the safety of bank deposits (Acharya and Mora, 2015). Given the ambiguous effects discussed above, in this paper, I control for liquidity holdings of banks, proxied by the ratio of cash and balances due from depository institutions to total assets (*liq*) and bank deposits, measured as the natural logarithm of total bank deposits (*lndep*).

The CAMELS rating system, employed by regulators to evaluate the safety and soundness of commercial banks, entails the assessment of the following six main areas: capital adequacy, asset quality, management capability, earnings, liquidity, and sensitivity to market risk. Each of the six components is rated by bank examiners on a scale from 1 (best) to 5 (worst) based on the financial statements and onsite examinations. These scores are then aggregated into a composite rating, represented by the acronym CAMELS. The values of CAMELS ratings are confidential and not available for this study. As stated above, I have controlled for bank liquidity, thus I introduce proxy variables for the remaining five dimensions. These five key measures of bank failure are, the ratio of equity capital to total assets as a proxy of capital adequacy (*ca*); the ratio of all nonperforming loans to total assets as a proxy of asset quality (*aq*); cost-to-income ratio as a proxy of management capability (*mc*); the ratio of net income to total equity as a proxy of earnings (*roe*); and loans-to-deposits ratio as a sensitivity measure to market risk (*ltdrt*).

Furthermore, this study employs the following ratios as controls: the ratio of non-interest income to total income (*noniirt*) as a measure of income diversification (DeYoung and Torna, 2013); the standard deviation of a bank's return on assets over the previous twelve quarters (*sd*) as a proxy for earning volatility (Berger and Bouwman, 2009); the Basel I risk-weighted assets of banks divided by total assets (*ristak*) as a measure of bank risk taking (Berger and Bouwman, 2013); and commercial real estate loans to total loans (*commre*) as a proxy for commercial real estate investment (Cole and White, 2012; Berger and Bouwman, 2013).

2.3.3.2 Macroeconomic and local market variables

This study employs the Federal funds rate (*fedfunds*) to control for the effect of monetary policy (Chatterjee, 2015). Following Imbierowicz and Rauch (2014), this study employs the spread between 3-month US T-Bills and 10-year US Treasuries (*spread*), the log of Gross Domestic Product (*lngdp*) and Gross Private Savings (*lngpsave*) as macro controls.

Loan demand depends on regional and nation-wide economic conditions as well as individual bank conditions. To control for varying levels of loan demand, this study employs the Senior Loan Officer Opinion Survey on Bank Lending Practices (*sloos*). The *sloos* data is available from 1982Q2 onwards and provides quarter-by-quarter national level reports of how strong the loan demand was based on observations of senior loan officers at the application desks. It includes information such as the net percentage of domestic banks reporting stronger demand for auto loans, credit card loans, government mortgage loans, commercial and industrial (C&I) loans etc. I use C&I loans because this variable has more valid observations than the other loans variables. The Herfindhal-Hirschman Index (*hhi_dep*) is used to measure the level of competition for deposits among banks in local markets (Tran, Lin and Nguyen, 2016). Per capita personal income (*lnperinc*), total employment (*lnemploy*) and total population (*lnpop*) are used as measures of county-level economic and demographic conditions. The definitions and abbreviations used for the main variables are contained in Appendix 2.2.

2.3.4 Descriptive statistics

Panel A of Table 2.1 contains summary statistics for main variables, while Panel B provides the correlation of these variables. Panel A of Table 2.1 shows that one, two, three and five-year bank failures (*bf1, bf2, bf3* and *bf5*) occurred in 0.5%, 1.1%, 1.6% and 2.6% of total bank-quarter observations, which means that there were 1,488, 3,274, 4,762, and 7,738 bank-quarter observations out of a total of 297,610 with one, two, three and five-year bank failures, respectively. The average bank liquidity creation normalized by gross total assets is 0.311 and 0.253 measured by *catfat* and *catnonfat* respectively. The mean value of capital adequacy (*ca*) indicates that the sample banks have strong capital positions. Panel B of Table 2.1 contains the Pearson correlation matrix of the variables applied in this study. The correlation coefficients are consistent with my main predictions. The coefficient between *catfat* and *catnonfat* is 0.96 and significant at the 1% level, indicating that these two measures of bank liquidity creation are highly correlated. As shown, without controlling for bank capital, both measures of liquidity creation (*catfat* and *catnonfat*) are positively and significantly correlated with all measures of bank failure. The data also shows that bank capital (*ca*) is negatively and significantly correlated with four measures of bank failure, implying that equity acts as a buffer against the probability of bank failure.

Table 2.1 Descriptive statistics and correlation matrix

Panel A: VARIABLES	(1) N	(2) Mean	(3) Sd	(4) Min	(5) P25	(6) P50	(7) P75	(8) Max
bf1	297,610	0.005	0.073	0.000	0.000	0.000	0.000	1.000
bf2	297,610	0.011	0.103	0.000	0.000	0.000	0.000	1.000
bf3	297,610	0.016	0.126	0.000	0.000	0.000	0.000	1.000
bf5	297,610	0.026	0.159	0.000	0.000	0.000	0.000	1.000
catfat	297,607	0.311	0.178	-0.155	0.196	0.322	0.435	0.718
catnonfat	297,607	0.253	0.154	-0.177	0.157	0.268	0.363	0.569
ca	297,607	0.108	0.036	0.049	0.086	0.100	0.120	0.272
Δ*ca*	297,609	6.95e-06	0.051	-0.171	-0.024	-3.33e-06	0.024	0.171
aq	297,609	0.003	0.005	-0.001	0.000	0.001	0.004	0.031
mc	297,566	0.784	0.169	0.479	0.689	0.761	0.842	1.637
roe	297,607	0.047	0.077	-0.363	0.021	0.046	0.084	0.230
liq	297,607	0.065	0.062	0.008	0.026	0.042	0.079	0.343
ltdrt	297,607	0.772	0.201	0.240	0.645	0.788	0.910	1.262
noniirt	297,472	0.852	1.744	-5.052	0.289	0.578	1.041	11.379
sd	288,670	3.930	3.064	0.607	2.251	3.201	4.509	20.726
ristak	297,609	0.689	0.132	0.342	0.604	0.699	0.782	0.976
commre	297,607	0.248	0.153	0.001	0.129	0.233	0.344	0.691
lndep	297,609	11.795	1.170	9.865	10.972	11.638	12.407	16.064
fedfunds	297,609	1.604	1.869	0.070	0.130	0.510	2.940	5.260
spread	297,607	2.036	1.140	-0.512	1.529	2.249	2.875	3.578
lngdp	297,607	9.581	0.115	9.339	9.502	9.587	9.667	9.786
lngpsave	297,607	7.961	0.181	7.702	7.787	7.922	8.137	8.230
crisisdummy	297,610	0.214	0.410	0.000	0.000	0.000	0.000	1.000
sloos	297,607	0.402	25.330	-60.400	-16.700	1.400	19.600	45.500
hhi_dep	297,607	0.476	0.299	0.027	0.250	0.402	0.620	1.000
lnperinc	297,508	10.450	0.263	9.898	10.267	10.432	10.611	11.243
lnemploy	297,508	10.693	1.939	7.351	9.207	10.223	12.138	15.496
lnpop	297,508	11.296	1.831	7.849	9.933	10.885	12.625	16.088

Note: There are two panels in this table. Panel A presents summary statistics for all variables used in the models. Panel B reports Pearson correlation matrix between variables. Bold and italicized coefficients are significant at p<0.001. See Appendix 2.2 for variable definitions.

Panel B: Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
(1)bf1	1.00																										
(2)bf2	**0.71**	1.00																									
(3)bf3	**0.58**	**0.82**	1.00																								
(4)bf5	**0.45**	**0.64**	**0.78**	1.00																							
(5)catfat	**0.03**	**0.05**	**0.06**	**0.09**	1.00																						
(6)catnonfat	**0.04**	**0.06**	**0.07**	**0.10**	**0.96**	1.00																					
(7)ca	**-0.09**	**-0.09**	**-0.09**	**-0.07**	**-0.26**	**-0.31**	1.00																				
(8)aq	**0.03**	**0.02**	**0.02**	**0.01**	-0.01	-0.00	0.00	1.00																			
(9)mc	**0.15**	**0.16**	**0.16**	**0.14**	**-0.06**	**-0.05**	**0.06**	**0.03**	1.00																		
(10)earn	**-0.25**	**-0.25**	**-0.23**	**-0.18**	**0.04**	**0.02**	**-0.06**	**-0.05**	**-0.64**	1.00																	
(11)liq	**0.01**	-0.01	**-0.02**	**-0.05**	**-0.13**	**-0.12**	**0.04**	**0.02**	**0.12**	**-0.13**	1.00																
(12)ltdrt	**0.03**	**0.06**	**0.08**	**0.11**	**0.70**	**0.70**	**-0.06**	**0.01**	**-0.02**	**0.01**	**-0.29**	1.00															
(13)noniirt	**-0.04**	**-0.04**	**-0.04**	**-0.04**	**0.03**	**0.02**	**-0.05**	-0.00	0.00	**0.06**	**0.06**	**-0.01**	1.00														
(14)sd	**0.22**	**0.21**	**0.19**	**0.16**	**0.05**	**0.05**	**0.10**	**0.02**	**0.21**	**-0.27**	**0.04**	**0.08**	**-0.13**	1.00													
(15)ristak	**0.05**	**0.08**	**0.11**	**0.14**	**0.76**	**0.74**	**-0.11**	**0.01**	**-0.01**	**-0.02**	**-0.26**	**0.77**	**-0.02**	**0.11**	1.00												
(16)commre	**0.05**	**0.06**	**0.07**	**0.07**	**0.21**	**0.23**	**-0.01**	**0.01**	**0.16**	**-0.16**	**0.06**	**0.13**	**0.03**	**0.08**	**0.15**	1.00											
(17)fedfunds	**-0.05**	**-0.04**	**-0.01**	**0.06**	**0.05**	**0.01**	**0.01**	**-0.13**	**-0.02**	**0.17**	**-0.27**	**0.12**	**-0.03**	**-0.01**	**0.11**	**-0.08**	1.00										
(18)spread	**0.05**	**0.04**	**0.01**	**-0.05**	**-0.05**	**-0.02**	**-0.02**	**0.13**	**0.03**	**-0.16**	**0.15**	**-0.06**	**0.02**	**0.02**	**-0.06**	**0.04**	**-0.86**	1.00									
(19)lngdp	**0.02**	**0.02**	**0.02**	-0.01	**0.02**	**0.04**	**0.03**	**0.03**	**0.03**	**-0.10**	**0.23**	**-0.08**	**0.01**	**0.01**	**-0.06**	**0.11**	**-0.37**	0.00	1.00								
(20)lngpsave	**0.05**	**0.04**	**0.02**	**-0.03**	**-0.01**	**0.02**	**0.01**	**0.10**	**0.04**	**-0.17**	**0.29**	**-0.11**	**0.02**	**0.03**	**-0.09**	**0.12**	**-0.68**	**0.34**	**0.87**	1.00							
(21)hhi_dep	0.00	**0.01**	0.00	0.00	**0.05**	**0.03**	**-0.01**	0.00	**-0.03**	-0.00	**0.01**	**0.02**	**0.02**	0.00	**0.02**	**0.03**	**-0.04**	**0.01**	**0.07**	**0.07**	1.00						
(22)lnpop	**0.05**	**0.07**	**0.09**	**0.11**	**0.29**	**0.26**	**0.02**	0.01	**0.20**	**-0.18**	**0.05**	**0.21**	**0.06**	**0.11**	**0.21**	**0.50**	0.00	-0.00	0.00	0.00	**0.07**	1.00					
(23)sloos	**-0.05**	**-0.07**	**-0.08**	**-0.04**	**0.02**	**0.02**	-0.00	**-0.12**	**-0.13**	**0.10**	**0.05**	**-0.07**	0.00	**-0.04**	**-0.07**	0.00	**0.23**	**-0.40**	**0.12**	**-0.02**	**0.01**	**-0.01**	1.00				
(24)lnperinc	**0.03**	**0.04**	**0.04**	**0.04**	**0.24**	**0.20**	**0.03**	**0.02**	**0.10**	**-0.12**	**0.14**	**0.09**	**0.02**	**0.06**	**0.13**	**0.22**	**-0.22**	**0.06**	**0.41**	**0.39**	**0.07**	**0.46**	**0.01**	1.00			
(25)lnemploy	**0.05**	**0.07**	**0.08**	**0.10**	**0.31**	**0.27**	**0.02**	0.00	**0.19**	**-0.17**	**0.04**	**0.22**	**0.06**	**0.11**	**0.22**	**0.48**	**0.01**	-0.01	0.00	0.00	**0.07**	**0.99**	**-0.01**	**0.52**	1.00		
(26)crisisdummy	**0.05**	**0.10**	**0.11**	**0.09**	**0.03**	**0.02**	**0.03**	**0.12**	**0.15**	**-0.07**	**-0.13**	**0.14**	**-0.01**	**0.05**	**0.14**	**-0.01**	**-0.08**	**0.16**	**0.03**	-0.00	**-0.01**	**0.02**	**-0.54**	**0.04**	**0.02**	1.00	
(27) lndep	0.00	0.00	0.00	-0.00	-0.00	0.00	0.01	**0.06**	0.00	**-0.02**	**0.04**	**-0.01**	0.00	-0.00	**-0.01**	**0.02**	**-0.08**	**0.03**	**0.14**	**0.14**	**0.01**	0.00	0.00	**0.06**	0.00	0.00	1.00

2.3.5 Econometric model

My baseline empirical model to examine the impact of bank liquidity creation on bank failure risk is described below.

$$
\begin{aligned}
&Bank\ Failure_{\ i,t} \\
&= \beta_0 + \beta_1 Liquidity\ Creation_{i,t-1} + \ \beta_2 Bank\ Characteristics_{i,t-1} \\
&+ \beta_3 Macroeconomic\ Characteristics_{i,t-1} \\
&+ \ \beta_4 Local\ Market\ Characteristics_{i,t-1} \\
&+ \Sigma Time, State\ and\ Bank\ Fixed\ Effects \\
&+ \varepsilon_{i,t} \qquad (3)
\end{aligned}
$$

In this equation, the dependent variable is *Bank Failure (bf)* and the main variable of interest is *Liquidity Creation*, proxied by BB measure, including *catfat* and *catnonfat.* I expect the coefficient on *Liquidity Creation*, β_1, to be negative and significant, indicating that higher levels of liquidity creation are associated with lower probability of bank failure due to the liquidity risk-sharing role of bank capital. I also control for bank-specific characteristics, macroeconomic conditions and local market influences; and ε is a random error term. Independent variables in the model are lagged one quarter with respect to the dependent variable to mitigate the potential endogeneity problem. All variables are discussed in detail in Section 2.3.2 and 2.3.3.

I estimate Eq. (3) empirically with the Ordinary Least Squares (OLS) method. [14] Fixed effects specification is recommended over random effects

[14] In the baseline specification, I use a linear model specification rather than the more commonly-used logit form. I do so for three reasons. First, logit model suffers incidental parameter bias and inconsistent estimation problem if fixed effects are included. That is, the inclusion of fixed effects in a logit specification would cause the number of parameters to grow with the number of observations, meaning that the parameter estimates cannot converge to their true value as the sample size increases, yielding biased parameter and standard error estimates (Wooldridge, 2010; Berger, Bouwman and Kim, 2017). Second, my focus is to find out what variables are useful in explaining bank failure rather than to forecast the predicted values of bank failure and therefore the issue of whether the predicted values may go beyond zero and one is not my concern. Third, note that Eq. (3) is only the baseline model, and the variable of interest is, as will be shown later, the interaction variable between bank capital and bank liquidity creation. In linear regressions, any interaction effect is fully captured by the coefficient on the interaction term, however, this does not carry over in nonlinear models such as the logit model (Berger and Bouwman, 2013). The literature on the interpretation of interaction term coefficients in logit (i.e. non-linear) regression estimations tells us that the statistical significance of the coefficient as well as its sign and magnitude cannot be interpreted in the same way as a coefficient of a linear regression. Instead, the direction of influence as well as the significance of the interaction term might vary across different

specification for the sample based on Hausman (1978) specification test results.[15] Fixed effects account for differences between banks, states and time. Justification for the inclusion of bank fixed effects is derived from the argument that unobserved, time-invariant bank-level heterogeneity exists and is not captured by control variables. The inclusion of year-quarter fixed effects captures factors specific to individual year-quarters. I also include state fixed effects to control for the influences of unknown time-invariant state-level factors. Standard errors are clustered at bank level to control for heteroskedasticity as well as possible serial correlation between observations of the same bank in different year-quarters.

2.4 Empirical analysis

2.4.1 Main results

Panel A (B) of Table 2.2 shows the main regression results of the OLS model as specified in Eq. (3) where *catfat* (*catnonfat*) is used. Six variants of Eq. (3) are specified, ranging from Model (1) where only bank specific variables and time dummies are included, to Model (6) where additional variables such as macroeconomic and local economic variables are also included. Panel A shows that the coefficient of *catfat* is negative and statistically significant across the six models, suggesting that bank liquidity creation is negatively associated with bank failure. I find that, using the coefficient from the full specification in Model (6) of Panel A, -0.030, as an illustration, one standard deviation increase in the *catfat* is associated with a 0.07 standard deviation decrease in the *bf* (-0.030*0.178/0.073). This coefficient also indicates that the likelihood of bank failure is 0.71% lower for banks that create liquidity in the 75th percentile than banks that create liquidity in the 25th percentile (1-exp(-0.030*0.435)/exp(-0.030*0.196)), ceteris paribus.

observations (Norton, Wang and Ai, 2004; Imbierowicz and Rauch, 2014). However, as shown in section 2.4.2, the results are largely the same when logit regression is used.

[15] Chi-squared=261.15 and *p*-value=0.000.

Turning to the control variables, I find that the coefficients largely have the predicted signs. Across all specifications, the coefficient on equity-to-assets ratio (*ca*) is economically and statistically significant and negatively related to bank failure *(bf1)*. This is consistent with my prediction that bank capital acts as a buffer to absorb risk stemming from liquidity creation and decrease the probability of bank failure. As expected, banks with better asset quality (*aq)*, higher earnings (*roe*), and more liquidity (*liq*) are less likely to fail, whereas banks that engage in excessive risk taking (*ristak*) and have more volatile earnings (*sd*) are more likely to fail. In general, I find that banks are less likely to fail in stronger economic and better local market conditions (*fedfunds, spread, lnpop, sloos, lnperinc* and *lnemploy*).

A similar conclusion can be drawn for *catnonfat* because the coefficient of *catnonfat* is consistently negative and statistically significant across the six models in Panel B. The only difference is that the magnitude of the coefficient is somewhat smaller compared to that of *catfat* in Panel A, indicating that the economic impact of on-balance sheet liquidity creation is weaker than that of total liquidity creation. Using the coefficient from the Model (6) of Panel B, -0.010, as an illustration, I find that one standard deviation increase in the *catnonfat* is associated with a 0.02 standard deviation decrease in the *bf* (-0.010*0.154/0.073) while the corresponding decrease in the *bf* is 0.07 for *catfat.*

Table 2.2 Baseline OLS regression

Panel A: VARIABLES	Model (1) *bf1*	Model (2) *bf1*	Model (3) *bf1*	Model (4) *bf1*	Model (5) *bf1*	Model (6) *bf1*
catfat	**-0.016*****	**-0.018*****	**-0.015*****	**-0.032*****	**-0.021*****	**-0.030*****
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
Bank-specific characteristics:						
ca	-0.277***	-0.275***	-0.278***	-0.429***	-0.279***	-0.421***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
aq	0.078**	0.097***	0.079**	0.074***	0.094***	0.069**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
mc	-0.024***	-0.014***	-0.024***	0.020***	-0.014***	0.011**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
roe	-0.254***	-0.220***	-0.254***	-0.174***	-0.218***	-0.209***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
liq	-0.010**	-0.014***	-0.010***	-0.013**	-0.018***	-0.012**
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
ltdrt	-0.005**	-0.004*	-0.005**	0.004	-0.001	0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
noniirt	0.000	-0.000	0.000	0.000*	-0.000	0.000**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
sd	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ristak	0.027***	0.030***	0.027***	0.024***	0.028***	0.022***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
commre	-0.000	-0.002	-0.002	0.000	-0.004**	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lndep	-0.000	-0.000	-0.000	0.000	-0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Macroeconomic characteristics:						
fedfunds		-0.003***	-0.001	-0.004***	-0.003***	0.011
		(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
spread		-0.004***	0.006	-0.004***	-0.004***	0.004
		(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
lngdp		-0.000	0.451**	0.027***	-0.002	0.360
		(0.00)	(0.19)	(0.00)	(0.00)	(0.24)
lngpsave		-0.014***	0.068***	-0.003	-0.012***	0.046
		(0.00)	(0.03)	(0.00)	(0.00)	(0.04)
Local economic characteristics:						
hhi_dep		0.000	0.000	0.000	0.000	0.000
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lnpop		0.004***	0.004***	-0.004*	0.003**	-0.003
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
sloos		-0.000***	0.000***	-0.000***	-0.000***	0.000***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lnperinc		-0.000	-0.000	-0.020***	0.001	-0.018***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lnemploy		-0.004***	-0.004***	0.005**	-0.003**	0.004*
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.037***	0.152***	-4.721**	-0.003	0.141***	-3.590
	(0.00)	(0.02)	(1.87)	(0.02)	(0.02)	(2.30)
Year_quarter FE	Yes	No	Yes	No	No	Yes
Bank FE	No	No	No	Yes	No	Yes
State FE	No	No	No	No	Yes	Yes
Observations	288,533	288,435	288,435	288,435	288,435	288,435
R-squared	0.112	0.107	0.113	0.106	0.110	0.111

Panel B: VARIABLES	Model (1) *bf1*	Model (2) *bf1*	Model (3) *bf1*	Model (4) *bf1*	Model (5) *bf1*	Model (6) *bf1*
catnonfat	**-0.013*****	**-0.015*****	**-0.013*****	**-0.013****	**-0.020*****	**-0.010***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
Bank-specific characteristics:						
ca	-0.276***	-0.274***	-0.276***	-0.416***	-0.278***	-0.406***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
aq	0.078**	0.098***	0.079**	0.081***	0.095***	0.070**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
mc	-0.024***	-0.014***	-0.024***	0.021***	-0.014***	0.012**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
roe	-0.254***	-0.220***	-0.255***	-0.175***	-0.219***	-0.210***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
liq	-0.011***	-0.015***	-0.011***	-0.015***	-0.018***	-0.013**
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
ltdrt	-0.006***	-0.004**	-0.006***	-0.003	-0.001	-0.006
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
noniirt	-0.000	-0.000	-0.000	0.000*	-0.000	0.000**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
sd	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ristak	0.023***	0.027***	0.024***	0.015***	0.025***	0.013***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
commre	-0.001	-0.002	-0.002	0.000	-0.003*	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lndep	-0.000	-0.000	-0.000	0.000	-0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Macroeconomic characteristics:						
fedfunds		-0.003***	-0.001	-0.004***	-0.003***	0.012
		(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
spread		-0.004***	0.006	-0.004***	-0.004***	0.004
		(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
lngdp		-0.001	0.458**	0.024***	-0.002	0.362
		(0.00)	(0.19)	(0.00)	(0.00)	(0.24)
lngpsave		-0.013***	0.070***	-0.002	-0.012***	0.041
		(0.00)	(0.03)	(0.00)	(0.00)	(0.04)
Local economic characteristics:						
hhi_dep		0.000	0.000	0.000	0.000	0.000
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lnpop		0.004***	0.004***	-0.004*	0.003**	-0.003
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
sloos		-0.000***	0.000***	-0.000***	-0.000***	0.000***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lnperinc		-0.001	-0.001	-0.021***	0.001	-0.019***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lnemploy		-0.004***	-0.004***	0.005**	-0.003**	0.004*
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.038***	0.159***	-4.796**	0.028	0.148***	-3.556
	(0.00)	(0.02)	(1.87)	(0.02)	(0.02)	(2.29)
Year_quarter FE	Yes	No	Yes	No	No	Yes
Bank FE	No	No	No	Yes	No	Yes
State FE	No	No	No	No	Yes	Yes
Observations	288,533	288,435	288,435	288,435	288,435	288,435
R-squared	0.112	0.107	0.113	0.106	0.110	0.110

Note: This table presents the results of multivariate OLS regression models in which the dependent variable is *Bank Failure* (*bf1*), a dummy that equals one if a bank fails within the next 12 months after a specific financial report date and zero otherwise. The key explanatory variable is *Bank Liquidity Creation*, proxied by BB measure (*catfat* in Panel A and *catnonfat* in Panel B). The variable descriptions are shown in Appendix 2.2. Regressions include different sets of controls and fixed effects (FE) estimations (Year_quarter FE, State FE and Bank FE) across Model (1)-(6). Robust standard errors clustered by bank are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

2.4.2 Non-linear model

To check the robustness of the results, I use the following multivariate logit regression framework that includes all the control variables from the baseline OLS regression model but with fixed effects excluded to avoid incidental parameter bias (see Section 2.3.5).

$$Prob(Bank\ Failure\ Indicatr = 1|X, Z) = \Lambda\left(\alpha + \beta X + \sum_{j=1}^{J} \gamma_j Z_j\right) \quad (4)$$

where $\Lambda(\mathrm{Y}) = \frac{e^Y}{1+e^Y} = \frac{\exp(Y)}{1+\exp(Y)}$, $\mathrm{Y} = \alpha + \beta X + \sum_{j=1}^{J} \gamma_j Z_j$; Λ denotes the cumulative logistic distribution function; X is the main test variable, namely the BB measure proxied by *catfat* or *catnonfat*; and Z represents the control variables. I compute marginal effects for the nonlinear model to ensure correct inference. Table 2.3 shows that the coefficients of *catfat* and *catnonfat* are again negative and highly significant, albeit slightly smaller in magnitude than those presented in Table 2.2.

Table 2.3 Non-linear (logit) regression

VARIABLES	(1) *bf1*	(2) *bf1*	(3) *bf1*	(4) *bf1*
catfat	**-0.010*****	**-0.009*****		
	(0.00)	(0.00)		
catnonfat			**-0.008*****	**-0.008*****
			(0.00)	(0.00)
Bank-specific characteristics:				
ca	-0.240***	-0.242***	-0.243***	-0.245***
	(0.02)	(0.02)	(0.02)	(0.02)
aq	0.114***	0.080***	0.118***	0.081***
	(0.02)	(0.02)	(0.02)	(0.02)
mc	0.005***	0.004***	0.005***	0.004***
	(0.00)	(0.00)	(0.00)	(0.00)
roe	-0.015***	-0.012***	-0.015***	-0.012***
	(0.00)	(0.00)	(0.00)	(0.00)
liq	-0.010***	-0.012***	-0.011***	-0.012***
	(0.00)	(0.00)	(0.00)	(0.00)
ltdrt	0.006***	0.005***	0.005**	0.005**
	(0.00)	(0.00)	(0.00)	(0.00)
noniirt	-0.000**	-0.000**	-0.000***	-0.000**
	(0.00)	(0.00)	(0.00)	(0.00)
sd	0.000***	0.000***	0.000***	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)
ristak	0.033***	0.031***	0.031***	0.030***
	(0.00)	(0.00)	(0.00)	(0.00)
commre	0.002	-0.002	0.002	-0.002
	(0.00)	(0.00)	(0.00)	(0.30)
lndep	0.000	-0.000	0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Macroeconomic characteristics:				
fedfunds		-0.003***		-0.003 ***
		(0.00)		(0.00)
spread		-0.001***		-0.001***
		(0.00)		(0.00)
lngdp		0.027***		0.026***
		(0.00)		(0.00)
lngpsave		-0.020***		-0.019***
		(0.00)		(0.00)
Local economic characteristics:				
hhi_dep		-0.000		-0.000
		(0.00)		(0.00)
lnpop		0.004***		0.004***
		(0.00)		(0.00)
sloos		-0.000***		-0.000***
		(0.00)		(0.00)
lnperinc		0.001		0.000
		(0.00)		(0.00)
lnemploy		-0.004***		-0.004***
		(0.00)		(0.00)
Constant	-8.867***	-35.795***	-8.613***	-35.222***
	(0.76)	(6.33)	(0.74)	(6.31)
Observations	288,533	288,435	288,533	288,435
Pseudo R-squared	0.495	0.519	0.494	0.518

Note: This table shows the marginal effects of logit regression models in which the dependent variable is *Bank Failure* (*bf1*), a dummy that equals one if a bank fails within the next 12 months after a specific financial report date and zero otherwise. The key explanatory variable is *Bank Liquidity Creation,* proxied by BB measure (*catfat* and *catnonfat*). The variable descriptions are in Appendix 2.2. I exclude all fixed effects to avoid incidental parameter bias. Robust standard errors clustered by bank are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

2.4.3 Alternative measures of bank failure

The robustness of the main findings is examined by using alternative time periods to measure bank failure risk. A bank is assigned the binary value of one if it fails within the next two, three, and five years of the financial report date. Otherwise, it is assigned the binary value of zero. The regression results presented in Panel A of Table 2.4 reinforce the prior findings. The coefficients on both *catfat* and *catnonfat* remain negative and statistically significant at the 1% level across all alternative measures of bank failure, and the magnitude of the coefficients is similar to that reported in the main results. For example, I find that one standard deviation increase in the *catfat* is associated with a 0.10, 0.10 and 0.05 standard deviation decrease in the *bf2*, *bf3* and *bf5* respectively (-0.059*0.178/0.103; -0.072*0.178/0.126; -0.042*0.178/0.159). I also present the results according to different sizes of banks, where large-, medium- and small-sized banks respectively have more than $3 billion, between $1 billion-$3 billion and up to $1 billion gross total assets. Consistent with the earlier findings, Panel B of Table 2.4 shows that the coefficients of *catfat* and *catnonfat* are negative and highly significant for small banks across different measures of bank failure, indicating that small banks tend to accumulate/maintain their capital as a precaution against liquidity risk arising from liquidity creation, which in turn reduces the likelihood of bank failure. By contrast, Panel C and D show that the coefficients of *catfat* and *catnonfat* are insignificant or weakly significant at the 5% or 10% level for medium and large banks. The possible explanation is that large and medium banks face lower levels of external financing constraints, and (for the largest, most inter-connected financial firms) tend to receive explicit and implicit government protection, therefore they may underestimate liquidity risk and are less likely to increase their capital accordingly.

Table 2.4 Alternative measures of bank failure

Panel A: Full sample VARIABLES	(1) *bf2*	(2) *bf3*	(3) *bf5*	(4) *bf2*	(5) *bf3*	(6) *bf5*
catfat	**-0.059*****	**-0.072*****	**-0.042*****			
	(0.01)	(0.01)	(0.01)			
catnonfat				**-0.027*****	**-0.041*****	**-0.032*****
				(0.01)	(0.01)	(0.01)
Bank-specific characteristics:						
ca	-0.555***	-0.543***	-0.304***	-0.533***	-0.524***	-0.300***
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
aq	0.013	0.046	0.005	0.013	0.046	0.005
	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)
mc	0.016**	0.020***	0.011**	0.018***	0.021***	0.012**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
roe	-0.252***	-0.224***	-0.121***	-0.254***	-0.227***	-0.123***
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
liq	-0.023***	-0.028***	-0.013*	-0.025***	-0.029***	-0.014*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ltdrt	0.020***	0.031***	0.021***	0.008	0.019**	0.017**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
noniirt	0.000	-0.000	-0.000**	0.000	-0.000	-0.000**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
sd	0.004***	0.004***	0.002***	0.005***	0.004***	0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ristak	0.037***	0.048***	0.050***	0.022***	0.032***	0.044***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
commre	0.001	-0.001	-0.003	0.001	-0.001	-0.003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lndep	-0.000	0.000	0.000	-0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Macroeconomic characteristics:						
fedfunds	0.011	0.012	-0.032	0.013	0.014	-0.031
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)
spread	-0.024	-0.016	-0.011	-0.024	-0.016	-0.010
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
lngdp	0.130	0.376	0.993	0.134	0.380	0.995
	(0.48)	(0.57)	(0.86)	(0.48)	(0.57)	(0.86)
lngpsave	0.167**	0.169**	0.122*	0.159**	0.161**	0.119*
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Local economic characteristics:						
hhi_dep	0.001**	0.001	0.001	0.001**	0.001	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lnpop	-0.000	0.001	0.003	-0.000	0.001	0.003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
sloos	0.001***	0.001***	0.000***	0.001***	0.001***	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lnperinc	-0.030***	-0.031***	-0.021***	-0.031***	-0.033***	-0.022***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lnemploy	0.003	0.001	-0.000	0.003	0.001	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-2.198	-4.528	-10.001	-2.167	-4.468	-9.981
	(4.35)	(5.36)	(8.16)	(4.34)	(5.36)	(8.17)
Year_quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	288,435	288,435	288,435	288,435	288,435	288,435
R-squared	0.110	0.092	0.054	0.108	0.091	0.053

Panel B: Small banks	(1)	(2)	(3)		(4)	(5)	(6)
VARIABLES	*bf2*	*bf3*	*bf5*		*bf2*	*bf3*	*bf5*
catfat	**-0.061*** **	**-0.074*** **	**-0.046*** **	***catnonfat***	**-0.026*** **	**-0.041*** **	**-0.036*** **
	(0.01)	(0.01)	(0.01)		(0.01)	(0.01)	(0.01)
Baseline Controls	Yes	Yes	Yes	Baseline Controls	Yes	Yes	Yes
Year_quarter FE	Yes	Yes	Yes	Year_quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Bank FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes	State FE	Yes	Yes	Yes
Observations	266,215	266,215	266,215	Observations	266,215	266,215	266,215
R-squared	0.110	0.092	0.052	R-squared	0.108	0.090	0.052

Panel C: Medium banks	(1)	(2)	(3)		(4)	(5)	(6)
VARIABLES	*bf2*	*bf3*	*bf5*		*bf2*	*bf3*	*bf5*
catfat	**-0.055**	**-0.070***	**-0.015**	***catnonfat***	**-0.029**	**-0.066***	**-0.019**
	(0.04)	(0.04)	(0.01)		(0.04)	(0.04)	(0.02)
Baseline Controls	Yes	Yes	Yes	Baseline Controls	Yes	Yes	Yes
Year_quarter FE	Yes	Yes	Yes	Year_quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Bank FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes	State FE	Yes	Yes	Yes
Observations	13,899	13,899	13,899	Observations	13,898	13,898	13,898
R-squared	0.097	0.059	0.029	R-squared	0.096	0.059	0.029

Panel D: Large banks	(1)	(2)	(3)		(4)	(5)	(6)
VARIABLES	*bf2*	*bf3*	*bf5*		*bf2*	*bf3*	*bf5*
catfat	**-0.057***	**-0.057**	**-0.003**	***catnonfat***	**-0.075****	**-0.073***	**-0.003**
	(0.03)	(0.04)	(0.02)		(0.03)	(0.04)	(0.03)
Baseline Controls	Yes	Yes	Yes	Baseline Controls	Yes	Yes	Yes
Year_quarter FE	Yes	Yes	Yes	Year_quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Bank FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes	State FE	Yes	Yes	Yes
Observations	8,321	8,321	8,321	Observations	8,320	8,320	8,320
R-squared	0.090	0.070	0.041	R-squared	0.090	0.070	0.041

Note: This table presents the results of multivariate OLS regression models in which the dependent variable is alternative measures of *Bank Failure* (*bf2, bf3* and *bf5*), a dummy that equals one if a bank fails within the next two, three, and five years of the financial report date and zero otherwise. The key explanatory variable is *Bank Liquidity Creation*, proxied by BB measure. Panel A shows the OLS results for full sample of banks. It is broken into subsamples of large, medium and small banks across Panel B-D. Large banks, medium banks, and small banks are banks with more than $3 billion, between $3 billion and $1 billion, and less than $1 billion gross total assets, respectively. I run all regressions separately for these three sets of banks. The variable descriptions are in Appendix 2.2. I report only specifications that include all the control variables and all fixed effects in this table. Robust standard errors clustered by bank are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

2.5 Additional analysis: bank capital channel

Determining the impact of bank capital on the relationship between liquidity creation and bank failure risk is the key issue in this paper since it reflects the liquidity-risk sharing role of bank capital. Specifically, banks that create more liquidity and are then exposed to higher liquidity risk may stockpile more capital as a precaution against illiquidity risk from bank liquidity creation. This would, in turn, lower the probability of bank failure. In this section, I perform additional analysis on bank capital as the channel through which bank liquidity creation affects bank failure risk.

I specify the following OLS regression to examine the moderating effect of changes in bank capital on the association between bank liquidity creation and bank failure risk.

$$
\begin{aligned}
&Bank\ Failure_{\ i,t} \\
&= \beta_0 + \beta_1 Liquidity\ Creation_{i,t-1} + \ \beta_2 Liquidity\ Creation_{i,t-1} \\
&\times \Delta Bank\ Capital_{i,t} + \beta_3 \Delta Bank\ Capital_{i,t} + \beta_4 Bank\ Characteristics_{i,t-1} \\
&+ \beta_5 Macroeconomic\ Characteristics_{i,t-1} \\
&+ \ \beta_6 Local\ Market\ Characteristics_{i,t-1} \\
&+ \Sigma Time, State\ and\ Bank\ Fixed\ Effects \\
&+ \varepsilon_{i,t} \qquad (5)
\end{aligned}
$$

I consider change in bank capital (Δ*Bank Capital*$_{i,t}$ = *Bank Capital*$_{i,t}$ – *Bank Capital*$_{i,t-1}$) since it is the extent of incremental changes in bank capital that really capture the risk sharing role. I include the interaction term in which *Liquidity Creation* is multiplied by Δ*Bank Capital* indicating how the effects of *Liquidity Creation* vary with the changes in bank capital over time. I also include Δ*Bank Capital* as an independent variable to capture any effects other than the liquidity risk sharing role of bank capital. The key variable of interest is the interaction term between *Liquidity Creation* and Δ*Bank Capital*. According to my hypothesis, the coefficient of the interaction term, β_2, is expected to be negative and significant, indicating that for banks with higher incremental increases in their capital ratios, higher liquidity creation is associated with lower probability of bank failure. Panel A and B of Table 2.5 summarize the regression results.

As shown in Panel A of Table 2.5, the coefficients of *catfat* are negative and statistically significant, indicating that liquidity creation negatively and significantly affects bank failure. This is similar to the results reported in Panel A of Table 2.2. Consistent with the hypothesis, I find that the coefficients of the interaction term of *catfat* with Δca are significantly negative in all specifications, suggesting that given the incremental increases in bank capital, bank liquidity creation negatively affects bank failure. A similar pattern is observed for *catnonfat*: the coefficients of the interaction variable are negative and statistically significant (see Panel B of Table 2.5). This result verifies the importance of the liquidity-risk sharing role of bank capital. In other words, bank capital acts as a buffer to absorb higher illiquidity risk from higher liquidity creation and lowers the probability of bank failure.

Table 2.5 The bank capital channel

Panel A: VARIABLES	(1) *bf1*	(2) *bf1*	(3) *bf1*	(4) *bf1*	(5) *bf1*
catfat	-0.019***	-0.017***	-0.031***	-0.023***	-0.028***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Δ*ca*	-0.450***	-0.483***	-0.572***	-0.448***	-0.586***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
catfat*Δca	**-0.850*** **	**-0.811*** **	**-0.530*** **	**-0.841*** **	**-0.516*** **
	(0.11)	(0.11)	(0.10)	(0.11)	(0.10)
Bank-specific characteristics:					
ca	-0.321***	-0.324***	-0.544***	-0.324***	-0.534***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
aq	0.080**	0.078**	0.061**	0.078**	0.069**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
mc	-0.023***	-0.033***	0.013***	-0.023***	0.004
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
roe	-0.224***	-0.258***	-0.173***	-0.222***	-0.207***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
liq	-0.009**	-0.004	-0.008	-0.012***	-0.006
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
ltdrt	-0.005**	-0.006***	0.001	-0.002	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
noniirt	0.000	0.000	0.000**	0.000	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
sd	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ristak	0.030***	0.026***	0.021***	0.028***	0.018***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
commre	-0.002	-0.002	0.001	-0.003*	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lndep	-0.000	-0.000	0.000	-0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Macroeconomic characteristics:					
fedfunds	-0.003***	-0.005	-0.004***	-0.003***	0.008
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
spread	-0.005***	0.007*	-0.004***	-0.004***	0.005
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
lngdp	0.000	0.513**	0.028***	-0.001	0.406
	(0.00)	(0.20)	(0.00)	(0.00)	(0.25)
lngpsave	-0.012***	0.041	-0.002	-0.011***	0.021
	(0.00)	(0.03)	(0.00)	(0.00)	(0.04)
Local economic characteristics:					
hhi_dep	0.000	0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lnpop	0.004***	0.004***	-0.004*	0.003**	-0.003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
sloos	-0.000***	0.000***	-0.000***	-0.000***	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lnperinc	-0.000	-0.000	-0.020***	0.001	-0.019***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lnemploy	-0.004***	-0.004***	0.005**	-0.003**	0.004*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.149***	-5.080***	0.002	0.139***	-3.782
	(0.02)	(1.91)	(0.02)	(0.02)	(2.33)
Year_quarter FE	No	Yes	No	No	Yes
Bank FE	No	No	Yes	No	Yes
State FE	No	No	No	Yes	Yes
Observations	288,435	288,435	288,435	288,435	288,435
R-squared	0.116	0.122	0.116	0.119	0.120

Panel B: VARIABLES	(1) *bf1*	(2) *bf1*	(3) *bf1*	(4) *bf1*	(5) *bf1*
catnonfat	-0.017***	-0.014***	-0.011**	-0.021***	-0.006
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
Δca	-0.303***	-0.338***	-0.458***	-0.301***	-0.474***
	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)
catnonfat*Δca	**-1.664***	**-1.606***	**-1.126***	**-1.649***	**-1.108***
	(0.14)	(0.14)	(0.12)	(0.14)	(0.12)
Bank-specific characteristics:					
ca	-0.314***	-0.317***	-0.523***	-0.319***	-0.512***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
aq	0.081**	0.077**	0.068**	0.079**	0.068**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
mc	-0.021***	-0.031***	0.015***	-0.021***	0.006
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
roe	-0.222***	-0.257***	-0.173***	-0.221***	-0.207***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
liq	-0.010**	-0.005	-0.010*	-0.013***	-0.006
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
ltdrt	-0.005***	-0.007***	-0.006	-0.002	-0.009**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
noniirt	-0.000	0.000	0.000**	0.000	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
sd	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ristak	0.026***	0.022***	0.011**	0.024***	0.008
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
commre	-0.001	-0.001	0.000	-0.003	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lndep	-0.000	-0.000	0.000	-0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Macroeconomic characteristics:					
fedfunds	-0.003***	-0.005*	-0.004***	-0.003***	0.009
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
spread	-0.004***	0.008*	-0.004***	-0.004***	0.005
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
lngdp	-0.000	0.529***	0.025***	-0.001	0.414*
	(0.00)	(0.20)	(0.00)	(0.00)	(0.25)
lngpsave	-0.012***	0.037	-0.001	-0.011***	0.012
	(0.00)	(0.03)	(0.00)	(0.00)	(0.04)
Local economic characteristics:					
hhi_dep	0.000	0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lnpop	0.004***	0.004***	-0.004*	0.003**	-0.003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
sloos	-0.000***	0.000***	-0.000***	-0.000***	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lnperinc	-0.001	-0.001	-0.021***	0.001	-0.019***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lnemploy	-0.004***	-0.004***	0.005**	-0.003**	0.004*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.152***	-5.195***	0.032	0.142***	-3.793
	(0.02)	(1.90)	(0.02)	(0.02)	(2.31)
Year_quarter FE	No	Yes	No	No	Yes
Bank FE	No	No	Yes	No	Yes
State FE	No	No	No	Yes	Yes
Observations	288,435	288,435	288,435	288,435	288,435
R-squared	0.117	0.123	0.116	0.120	0.121

Note: This table presents the results of multivariate OLS regression models Eq. (5) analysing the effects of bank capital on the relationship between *Bank Liquidity Creation* (*catfat* in Panel A and *catnonfat* in Panel B) and *Bank Failure Risk* (*bf1*), a dummy that equals one if a bank fails within the next 12 months after a specific financial report date and zero otherwise. Change in Bank Capital ($\Delta ca_{i,t}$) is the absolute change from the year *t-1* to *t* of bank *i*'s equity-to-total assets ratio. I examine the indirect/moderating effects of bank capital by including the interaction term between bank liquidity creation and changes in capital ratio. The variable descriptions are in Appendix 2.2. Regressions include different fixed effects (FE) estimations (Year_quarter FE, State FE and Bank FE) across Model (2)-(5). Robust standard errors clustered by bank are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

2.6 Robustness checks

This section presents the results for a number of robustness checks that yield interesting insights into the incremental effect of bank capital. Specifically, I examine the robustness of these main findings about the bank capital channel in terms of (1) different bank size groups; (2) crisis vs. non-crisis periods; (3) endogeneity issue; and (4) different bank capital measures. The same control variables that are used in the main regressions are included with some exceptions mentioned below. It can be seen that the findings are qualitatively similar to the main results.

2.6.1 Size effect

I re-estimate the OLS regression model in Section 2.5 using subsamples of banks based on different size cutoffs. I split the sample based on bank size because liquidity creation differs considerably among different sizes of banks (Berger and Bouwman, 2009). More importantly, size difference may have an impact on the likelihood of bank failure through the bank capital channel. For example, Berger and Bouwman (2013) found that capital helps to enhance the survival likelihood of small banks at all times (during banking crises, market crises, and normal times) while it helps medium and large banks primarily during banking crises. First, following the methodology of Berger and Bouwman (2009), the sample is split into large banks (GTA exceeding $3 billion), medium banks (GTA between $1 billion and $3 billion), and small banks (GTA up to $1 billion). Second, I use alternative cutoff ($5 billion and $10 billion, respectively) separating medium and large banks while small-bank definition remains $1 billion cutoff. Third, I run regressions categorising all banks as either small or large using a cutoff of $10 billion GTA. Finally, very large banks may be considered too-big-to-fail (TBTF), and in the event of distress, they tend to receive government support. To make sure that my large-bank results are not overly influenced by TBTF banks, I re-run the $10 billion cutoff analyses while excluding these banks. Following the 2010 Dodd-Frank Act, I define TBTF banks as those with GTA exceeding $50 billion.

As shown in Table 2.6, the coefficients on *catfat* and *catnonfat* are highly and statistically significant for small banks while they are insignificant or weakly significant for medium and large banks, indicating that the negative effects of liquidity creation on bank failure are more prominent for small banks. Table 2.6 also shows that the coefficients on the interaction terms $catfat \times \Delta ca$ and $catnonfat \times \Delta ca$ remain negative and statistically significant in all subsamples of small banks, but they are not statistically significant for large banks in most specifications. This is not surprising given that access to external funds is limited for small banks. Allen, Peristiani and Saunders (1989) argue that small banks face greater information asymmetry which makes it costly for them to access the interbank market. They, therefore, have strong incentives of hoarding capital/cash to avoid financing constraints and costly default. Thus, small banks may increase their capital ratios when they face higher illiquidity stemming from liquidity creation (Distinguin, Roulet and Tarazi, 2013). This would, in turn, lower the probability of bank failure. In contrast, large banks can more easily access funding from national or international capital markets, incur lower expected costs of raising new equity on short notice, and (for the largest, most inter-connected financial firms) may have access to explicit and implicit government protection. Therefore they may underestimate liquidity risk and be less likely to strengthen their capital accordingly. Similar to Berger and Bouwman (2009), I find that for medium-size banks the coefficient on the interaction term $catnonfat \times \Delta ca$ is, similar to that of small banks, negative and statistically significant but the coefficient on the interaction term $catfat \times \Delta ca$ is insignificant across all subsamples, which is similar to that of large banks.

Table 2.6 Results of OLS estimates sorted by bank size

Panel A: $1 billion and $3 billion size cutoff	(1)	(2)	(3)		(4)	(5)	(6)
	Small banks	Medium banks	Large banks		Small banks	Medium banks	Large banks
VARIABLES	*bf1*	*bf1*	*bf1*		*bf1*	*bf1*	*bf1*
catfat	**-0.030*****	**-0.027**	**-0.038***	***catnonfat***	**-0.012****	**-0.026**	**-0.037**
	(0.01)	(0.02)	(0.02)		(0.01)	(0.02)	(0.02)
Δca	-0.586***	-0.913**	-0.842***	Δca	-0.443***	-0.492*	-0.452**
	(0.04)	(0.39)	(0.30)		(0.04)	(0.30)	(0.18)
catfat*Δca	**-0.565*****	**-0.789**	**0.865**	***catnonfat*Δca***	**-1.171*****	**-2.345****	**-0.102**
	(0.10)	(0.86)	(0.41)		(0.12)	(0.95)	(0.38)
Baseline Controls	Yes	Yes	Yes	Baseline Controls	Yes	Yes	Yes
Year_quarter FE	Yes	Yes	Yes	Year_quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Bank FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes	State FE	Yes	Yes	Yes
Observations	266,215	13,899	8,321	Observations	266,215	13,899	8,321
R-squared	0.121	0.144	0.106	R-squared	0.155	0.242	0.173

Panel B: $1 billion and $5 billion size cutoff	(1)	(2)	(3)		(4)	(5)	(6)
	Small banks	Medium banks	Large banks		Small banks	Medium banks	Large banks
VARIABLES	*bf1*	*bf1*	*bf1*		*bf1*	*bf1*	*bf1*
catfat	**-0.030*****	**-0.028**	**-0.004**	***catnonfat***	**-0.012****	**-0.035***	**-0.002**
	(0.01)	(0.02)	(0.02)		(0.01)	(0.02)	(0.03)
Δca	-0.586***	-1.042**	-0.592*	Δca	-0.443***	-0.555**	-0.359*
	(0.04)	(0.36)	(0.33)		(0.04)	(0.25)	(0.19)
catfat*Δca	**-0.565*****	**-0.180**	**0.763***	***catnonfat*Δca***	**-1.171*****	**-1.840****	**0.371**
	(0.10)	(0.74)	(0.46)		(0.12)	(0.80)	(0.33)
Baseline Controls	Yes	Yes	Yes	Baseline Controls	Yes	Yes	Yes
Year_quarter FE	Yes	Yes	Yes	Year_quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Bank FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes	State FE	Yes	Yes	Yes
Observations	266,215	16,352	5,868	Observations	266,215	16,352	5,868
R-squared	0.121	0.139	0.080	R-squared	0.155	0.251	0.167

Panel C: $1 billion and $10 billion size cutoff	(1)	(2)	(3)		(4)	(5)	(6)
	Small banks	Medium banks	Large banks		Small banks	Medium banks	Large banks
VARIABLES	*bf1*	*bf1*	*bf1*		*bf1*	*bf1*	*bf1*
catfat	**-0.030*****	**-0.028**	**-0.031**	***catnonfat***	**-0.012****	**-0.032***	**-0.030**
	(0.01)	(0.02)	(0.02)		(0.01)	(0.02)	(0.02)
Δca	-0.586***	-1.018***	-0.326	Δca	-0.443***	-0.606**	-0.160
	(0.04)	(0.32)	(0.23)		(0.04)	(0.24)	(0.12)
catfat* $\boldsymbol{\Delta ca}$	**-0.565*****	**-0.144**	**0.342**	***catnonfat**** $\boldsymbol{\Delta ca}$	**-1.171*****	**-1.565****	**-0.124**
	(0.10)	(0.66)	(0.26)		(0.12)	(0.74)	(0.21)
Baseline Controls	Yes	Yes	Yes	Baseline Controls	Yes	Yes	Yes
Year_quarter FE	Yes	Yes	Yes	Year_quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Bank FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes	State FE	Yes	Yes	Yes
Observations	266,215	18,387	3,833	Observations	266,215	18,387	3,833
R-squared	0.121	0.142	0.045	R-squared	0.155	0.220	0.101

Panel D: $10 billion size cutoff	(1) Small banks	(2) Large banks with TBTF banks*	(3) Large banks without TBTF banks		(4) Small banks	(5) Large banks with TBTF banks*	(6) Large banks without TBTF banks
VARIABLES	*bf1*	*bf1*	*bf1*		*bf1*	*bf1*	*bf1*
catfat	**-0.030*****	**-0.031**	**-0.065**	***catnonfat***	**-0.015*****	**-0.030**	**-0.055**
	(0.00)	(0.02)	(0.05)		(0.00)	(0.02)	(0.04)
Δca	-0.602***	-0.326	-0.442	Δca	-0.450***	-0.160	-0.249
	(0.04)	(0.23)	(0.31)		(0.04)	(0.12)	(0.18)
catfat**Δca**	**-0.560*****	**0.342**	**0.316**	***catnonfat*****Δca**	**-1.205*****	**-0.124**	**-0.155**
	(0.10)	(0.26)	(0.34)		(0.12)	(0.21)	(0.31)
Baseline Controls	Yes	Yes	Yes	Baseline Controls	Yes	Yes	Yes
Year_quarter FE	Yes	Yes	Yes	Year_quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Bank FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes	State FE	Yes	Yes	Yes
Observations	284,602	3,833	2,353	Observations	284,602	3,833	2,353
R-squared	0.123	0.045	0.082	R-squared	0.159	0.101	0.082

*TBTF banks = “too-big-to-fail” bank

Note: This table presents the results of OLS models analysing Eq. (5) analysing the effects of bank capital on the relationship between *Bank Liquidity Creation* (*catfat* and *catnonfat*) and *Bank Failure Risk* (*bf1*), a dummy that equals one if a bank fails within the next 12 months after a specific financial report date and zero otherwise across three subsamples. Change in Bank Capital ($\Delta ca_{i,t}$) is the absolute change from the year *t-1* to *t* of bank *i*’s equity-to-total assets ratio. I sort the sample banks into large, medium and small banks based on different size cutoffs across Panel A-D. The variable descriptions are in Appendix 2.2. For brevity, I report only specifications that include all the control variables and all fixed effects in this table. Robust standard errors clustered by bank are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

2.6.2 Crisis vs. non-crisis periods

The financial turmoil started in August 2007 when asset-backed securities, particularly those backed by subprime mortgages, suddenly became illiquid and fell sharply in value. In fact, a record housing boom turned into a housing bust. A significant, but relatively mild, financial disruption was transformed into a full-fledged financial crisis with the Lehman bankruptcy on September 15, 2008. It led to a large increase in uncertainty and a wave of distressed selling of mortgage backed securities that started experiencing huge losses. Consequently, banks held higher capital levels to strengthen their solvency and to better assume losses arising from forced early liquidation of illiquid assets at fire sale prices. Therefore, it is expected that bank capital plays a more prominent role in alleviating the illiquidity risk of liquidity creation during the crisis period than during the non-crisis period. I examine how the effects of *Liquidity Creation* on *Bank Failure* vary with the changes in bank capital during the recent financial crisis period using a triple interaction term in the following regression model:

$$
\begin{aligned}
&Bank\ Failure_{\ i,t} \\
&= \beta_0 + \beta_1 Liquidity\ Creation_{i,t-1} \\
&+\ \beta_2 \Delta Bank\ Capital_{i,t} + \beta_3 Crisisdummy_t + \beta_4 Liquidity\ Creation_{i,t-1} \\
&\times Crisisdummy_t + \beta_5 Liquidity\ Creation_{i,t-1} \times \Delta Bank\ Capital_{i,t} \\
&+ \beta_6 Crisisdummy_t \times \Delta Bank\ Capital_{i,t} + \beta_7 Liquidity\ Creation_{i,t-1} \\
&\times \Delta Bank\ Capital_{i,t} \times Crisisdummy_t + \beta_8 Bank\ Characteristics_{i,t-1} \\
&+ \beta_9 Macroeconomic\ Characteristics_{i,t-1} \\
&+\ \beta_{10} Local\ Market\ Characteristics_{i,t-1} \\
&+ \Sigma Time, State\ and\ Bank\ Fixed\ Effects \\
&+ \varepsilon_{i,t} \qquad (6)
\end{aligned}
$$

The main variable of interest is the triple interaction term, i.e., *Liquidity* $Creation_{i,t-1} \times \Delta Bank\ Capital_{i,t} \times Crisisdummy_t$. A negative coefficient on *Liquidity Creation* implies that higher liquidity creation is associated with lower probability of bank failure. Therefore, negative signs on the triple interaction term would suggest that the marginal effect of *Liquidity Creation* on *Bank Failure* is stronger for banks with higher incremental increase in capital during the financial crisis period than during the non-crisis period. Following existing literature (Berger and Bouwman, 2013; Díaz and Huang, 2017; Tran, Lin and Nguyen, 2016), I assigned the *Crisisdummy* variable a value of one from the third quarter of 2007 to the fourth quarter of 2009, and zero otherwise. Table 2.7 contains the crisis regression results.

As shown in Panel A and B of Table 2.7, the coefficients on the triple interaction terms, $catfat \times \Delta ca \times crisisdummy$ and $catnonfat \times \Delta ca \times crisisdummy$, are large, negative, and highly statistically significant and economically non-trivial across all specifications. It implies that during the financial crisis, bank liquidity creation is negatively related to bank failure for banks with higher incremental increases in bank capital. I also find that the coefficients of the interaction term $crisisdummy \times \Delta ca$ are negative and statistically significant, indicating that for banks with higher incremental increases in bank capital, the crisis period negatively affects bank failure. Furthermore, the positive and statistically significant coefficients of the interaction term $catnonfat \times crisisdummy$, as opposed to the positive but insignificant coefficients of the interaction term $catfat \times crisisdummy$ indicate that in the absence of any changes in bank capital, on-balance sheet bank liquidity creation is the major contributor of bank failure risk during the crisis period. This is not surprising given the pressure on bank balance sheets from takedowns of pre-existing loan commitments. As is well known, an off-balance sheet loan commitment becomes an on-balance sheet loan when the borrower chooses to draw on their credit lines. When the supply of overall market liquidity falls, as during the recent financial crisis, borrowers turn to banks *en masse* to draw funds from existing credit lines (Gatev and Strahan, 2006). Thus, the higher on-balance sheet liquidity creation by a bank, the higher the liquidity and failure risk that the bank is exposed to. Finally, consistent with the results in Table 2.5, the coefficients of the interaction terms of *catfat* with Δca and *catnonfat* with Δca are significantly negative for most specifications, suggesting that given the incremental increases in bank capital, bank liquidity creation negatively affects bank failure. In particular, the effect is more pronounced for on-balance sheet liquidity creation as it heavily exposes banks to liquidity risk due to the pressure on bank on-balance sheet. Therefore, bank capital plays a prominent role in absorbing liquidity risk from on-balance sheet liquidity creation.

Table 2.7 Results of OLS estimates during the recent financial crisis

Panel A: VARIABLES	(1) *bf1*	(2) *bf1*
catfat	-0.028***	-0.028***
	(0.01)	(0.01)
Δca	-0.519***	-0.521***
	(0.04)	(0.04)
crisisdummy	0.006***	-0.080
	(0.00)	(0.07)
catfat×crisisdummy	0.005	0.004
	(0.00)	(0.00)
catfat×Δca	-0.162*	-0.148
	(0.09)	(0.09)
crisisdummy×Δca	-0.334***	-0.345***
	(0.09)	(0.09)
catfat×Δca×crisisdummy	**-1.413*** **	**-1.468*** **
	(0.30)	(0.30)
Bank-specific characteristics:		
ca	-0.540***	-0.542***
	(0.03)	(0.03)
aq	0.066**	0.068**
	(0.03)	(0.03)
mc	0.000	0.001
	(0.01)	(0.01)
roe	-0.208***	-0.208***
	(0.01)	(0.01)
liq	-0.004	-0.006
	(0.01)	(0.01)
ltdrt	-0.003	-0.003
	(0.00)	(0.00)
noniirt	0.000***	0.000***
	(0.00)	(0.00)
sd	0.004***	0.004***
	(0.00)	(0.00)
ristak	0.016***	0.016***
	(0.01)	(0.01)
commre	0.002	0.001
	(0.00)	(0.00)
lndep	0.000	0.000
	(0.00)	(0.00)
Macroeconomic characteristics:		
fedfunds		0.004
		(0.01)
spread		0.006
		(0.01)
lngdp		0.459*
		(0.25)
lngpsave		-0.004
		(0.05)
Local economic characteristics:		
hhi_dep		0.000
		(0.00)
lnpop		-0.003
		(0.00)
sloos		0.000***
		(0.00)
lnperinc		-0.019***
		(0.00)
lnemploy		0.004*
		(0.00)
Constant	0.041***	-4.065*
	(0.01)	(2.33)
Year_quarter FE	Yes	Yes
Bank FE	Yes	Yes
State FE	Yes	Yes
Observations	288,533	288,435
R-squared	0.122	0.123

Panel B: VARIABLES	(1) *bf1*	(2) *bf1*
catnonfat	-0.005	-0.006
	(0.01)	(0.01)
Δca	-0.420***	-0.423***
	(0.03)	(0.03)
crisisdummy	0.007***	-0.076
	(0.00)	(0.07)
catnonfat×crisisdummy	0.009**	0.008**
	(0.00)	(0.00)
catnonfat×Δca	-0.583***	-0.562***
	(0.11)	(0.11)
crisisdummy×Δca	-0.287***	-0.295***
	(0.07)	(0.07)
catnonfat*×Δca×*crisisdummy	**-2.147*** **	**-2.228*** **
	(0.38)	(0.39)
Bank-specific characteristics:		
ca	-0.516***	-0.518***
	(0.03)	(0.03)
aq	0.066**	0.067**
	(0.03)	(0.03)
mc	0.003	0.004
	(0.01)	(0.01)
roe	-0.208***	-0.208***
	(0.01)	(0.01)
liq	-0.005	-0.006
	(0.01)	(0.01)
ltdrt	-0.012***	-0.011***
	(0.00)	(0.00)
noniirt	0.000***	0.000***
	(0.00)	(0.00)
sd	0.004***	0.004***
	(0.00)	(0.00)
ristak	0.005	0.005
	(0.01)	(0.01)
commre	0.002	0.001
	(0.00)	(0.00)
lndep	0.000	0.000
	(0.00)	(0.00)
Macroeconomic characteristics:		
fedfunds		0.005
		(0.01)
spread		0.006
		(0.01)
lngdp		0.474*
		(0.25)
lngpsave		-0.019
		(0.05)
Local economic characteristics:		
hhi_dep		0.000
		(0.00)
lnpop		-0.003
		(0.00)
sloos		0.001***
		(0.00)
lnperinc		-0.019***
		(0.00)
lnemploy		0.004*
		(0.00)
Constant	0.024***	-4.099*
	(0.01)	(2.31)
Year_quarter FE	Yes	Yes
Bank FE	Yes	Yes
State FE	Yes	Yes
Observations	288,533	288,435
R-squared	0.122	0.124

Note: This table presents the results of multivariate OLS regression models analysing Eq. (6) in which the dependent variable is *Bank Failure* (*bf1*), a dummy that equals one if a bank fails within the next 12 months after a specific financial report date and zero otherwise. The key explanatory variable are the triple interaction terms *catfat*×Δca×*crisisdummy* and *catnonfat*×Δca×*crisisdummy*. *Bank Liquidity Creation* is proxied by BB measure (*catfat* in Panel A and *catnonfat* in Panel B). *Crisisdummy* is a dummy variable equal to one during 2007:Q3-2009:Q4, and zero otherwise. Change in Bank Capital ($\Delta ca_{i,t}$) is the absolute change from the year *t-1* to *t* of bank *i*'s equity-to-total assets ratio. Column (1) includes bank-specific characteristics only as control variables while Column (2) includes all controls, i.e., bank characteristics, macroeconomic and local economic conditions. The variable descriptions are in Appendix 2.2. Robust standard errors clustered by bank are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

2.6.3 Controlling for endogeneity

Empirical banking research may be afflicted by the potential endogeneity problem, and this study is no exception. The main objective of this paper is to study the effect of bank liquidity creation on failure risk. In doing so, liquidity creation is treated as exogenously given. But it is known that in practice, banks may choose their liquidity policy endogenously. Two main causes can give rise to the endogeneity problem in this study. First, the relation may be driven by omitted variables that are correlated with both bank liquidity and failure risk. One potential candidate for omitted variables is bank governance factors which are relevant but unobservable. For example, bank CEO compensation depends on executive abilities, which are difficult to quantify and observe. Second, measurement errors may also give rise to endogeneity problems. Any discrepancy between the true variable of interest and the proxy leads to measurement error. For example, because CAMELS ratings are confidential, I use proxy variables for each of the six categories of the CAMELS rating system about the financial condition and performance of banks. However, it is also possible that they are measured with errors and do not capture the true content of onsite examinations since banking regulators may use other intangible or undeclared criteria to assess the financial health of banks. The impact of the endogeneity problem on the regression results is based on the extent to which the omitted variables or measurement errors drive both liquidity creation and bank failure.

My results are based on one-quarter lagged values of all independent variables and the use of fixed effects which allow me to partly address the potential endogeneity. However, this might not be enough because of intertemporal rigidities in some of these variables. To address this endogeneity issue more directly, I estimate the model using the two-stage least squares (2SLS) instrumental variable (IV) approach. In this study, three-quarter lagged average values of bank liquidity creation (*catfat_average* and *catnonfat_average*) are used as the instrumental variables, since lagged values are more likely to reflect earlier bank decisions and may not directly affect the contemporaneous failure risk. The use of a three-quarter average, rather than a single lagged quarter value, may reduce the effect of short-term fluctuations and problems with the use of accounting data (Berger and Bouwman, 2009). Identification of the IV model requires a strong correlation between the instrument and the endogenous variable. It is reasonable to expect that a three-quarter lagged average value of bank liquidity creation is highly correlated with the contemporaneous bank liquidity creation. For the instrument to be valid it should not be affected by the dependent variable, and not affect the dependent variable except through the endogenous variable. It is unlikely that the failure risk of the bank affects the three-quarter lagged average values of bank liquidity creation. Also it is unlikely that the three-quarter lagged average value of a bank's liquidity creation affects the bank's failure risk except through its effect on contemporaneous bank liquidity creation, satisfying the exclusion restriction. The statistical tests validate the choice of the instrument and indicate robustness. Endogeneity test shows that the bank liquidity creation measure is indeed endogenous. Kleibergen-Paap Wald rk F statistic shows that the instrument is relevant and do no suffer from weak instrument concerns.

Table 2.8 presents the results of the 2SLS model. Column (1) of Panel A and B reports the first-stage regressions. In both regressions, the coefficients for the instrumental variables, *catfat_average* and *catnonfat_average*, are positive and statistically significant. Column (2) of Panel A and B reports the second-stage regressions in which *Bank Failure Risk* is the dependent variable. The negative and statistically significant coefficients on $catfat \times \Delta ca$ and $catnonfat \times \Delta ca$ in Column (2) provide support for my hypothesis. In other words, given the incremental increases in bank capital, bank liquidity creation negatively affects bank failure. When I instrument *catfat* with *catfat_average* (or *catnonfat* with *catnonfat_average*), the estimated coefficients of $catfat \times \Delta ca$ and $catnonfat \times \Delta ca$ increase from -0.516 (Column (5) of Panel A, Table 2.5) to -0.695 and from -1.108 (Column (5) of Panel B, Table 2.5) to -1.462 respectively and are highly statistically significant. The 2SLS coefficients are larger than the OLS coefficients, a common finding in the literature (Berger and Sedunov, 2017). Overall, the IV estimates broadly confirm my earlier results, suggesting that the findings are not the product of an endogeneity bias.

Table 2.8 The effect of bank liquidity creation on bank failure in a 2SLS setting

Panel A:	(1) First stage	(2) Second stage
VARIABLES	DV=Bank Liquidity Creation (*catfat*)	DV=Bank Failure Risk (*bf1*)
catfat		-0.027***
		(0.01)
catfat*×Δ*ca	3.639***	**-0.695*** **
	(0.19)	(0.09)
Δ*ca*	-1.504***	-0.578***
	(0.07)	(0.03)
catfat_average	**0.498*** **	
	(0.00)	
Bank-specific characteristics:		
ca	0.023**	-0.527***
	(0.10)	(0.01)
aq	0.01	0.069**
	(0.02)	(0.03)
mc	0.01***	0.004
	(0.00)	(0.00)
roe	0.045***	-0.206***
	(0.00)	(0.01)
liq	-0.004	-0.006*
	(0.00)	(0.00)
ltdrt	0.019***	-0.007***
	(0.00)	(0.00)
noniirt	-0.000	0.000***
	(0.00)	(0.00)
sd	-0.000***	0.004***
	(0.00)	(0.00)
ristak	0.222***	0.018***
	(0.00)	(0.00)
commre	0.003**	0.001
	(0.00)	(0.00)
lndep	-0.000	0.000
	(0.00)	(0.00)
Macroeconomic characteristics:		
fedfunds	-0.053	0.008
	(0.04)	(0.01)
spread	0.002	0.005
	(0.01)	(0.01)
lngdp	-0.110	0.410
	(0.28)	(0.26)
lngpsave	0.095	0.017
	(0.08)	(0.04)
Local economic characteristics:		
hhi_dep	-0.001*	0.000
	(0.00)	(0.00)
lnpop	-0.006***	-0.003*
	(0.00)	(0.00)
sloos	-0.000***	0.000***
	(0.00)	(0.00)
lnperinc	0.010***	-0.019***
	(0.00)	(0.00)
lnemploy	0.006***	0.004***
	(0.00)	(0.00)
Constant	0.114	-2.829
	(2.64)	(2.21)
Year_quarter FE	Yes	Yes
Bank FE	Yes	Yes
State FE	Yes	Yes
Observations	288,301	288,301
R-squared	0.510	0.121
Kleibergen-Paap Wald rk F statistic	F-stat= 12675.72, *p*-value=0.000	
Endogeneity test	Chi-stat= 26.86, *p*-value= 0.000	

Panel B:	(1) First stage	(2) Second stage
VARIABLES	DV=Bank Liquidity Creation (*catnonfat*)	DV=Bank Failure Risk (*bf1*)
catnonfat		-0.016***
		(0.01)
catnonfat×Δca	4.126***	**-1.462*** **
	(0.20)	(0.12)
Δ*ca*	-1.419***	-0.460***
	(0.06)	(0.03)
catnonfat_average	**0.473*** **	
	(0.00)	
Bank-specific characteristics:		
ca	-0.126***	-0.519***
	(0.01)	(0.01)
aq	0.012	0.069**
	(0.02)	(0.03)
mc	0.003*	0.004
	(0.00)	(0.00)
roe	0.009***	-0.207***
	(0.00)	(0.01)
liq	-0.011**	-0.006*
	(0.00)	(0.00)
ltdrt	0.056***	-0.009***
	(0.00)	(0.00)
noniirt	-0.000	0.000***
	(0.00)	(0.00)
sd	-0.000*	0.004***
	(0.00)	(0.00)
ristak	0.142***	0.011***
	(0.00)	(0.00)
commre	0.008***	0.001
	(0.00)	(0.00)
lndep	-0.000	0.000
	(0.00)	(0.00)
Macroeconomic characteristics:		
fedfunds	-0.059	0.009
	(0.04)	(0.01)
spread	0.001	0.005
	(0.01)	(0.01)
lngdp	-0.054	0.425*
	(0.28)	(0.26)
lngpsave	0.063	0.007
	(0.07)	(0.04)
Local economic characteristics:		
hhi_dep	-0.000	0.000
	(0.00)	(0.00)
lnpop	-0.007***	-0.003*
	(0.00)	(0.00)
sloos	-0.000***	0.000***
	(0.00)	(0.00)
lnperinc	-0.008***	-0.020***
	(0.00)	(0.00)
lnemploy	0.008***	0.004**
	(0.00)	(0.00)
Constant	0.289	-3.036
	(2.55)	(2.21)
Year_quarter FE	Yes	Yes
Bank FE	Yes	Yes
State FE	Yes	Yes
Observations	288,301	288,301
R-squared	0.515	0.121
Kleibergen-Paap Wald rk F statistic	F-stat= 15461.15, *p*-value=0.000	
Endogeneity test	Chi-stat= 6.77, *p*-value= 0.009	

Note: This table reports the results of two-stage least squares (2SLS) regression analysis testing the effects of bank capital on the relationship between bank liquidity creation (*catfat* in Panel A and *catnonfat* in Panel B) and bank failure risk (*bf1*), a dummy that equals one if a bank fails within the next 12 months after a specific financial report date and zero otherwise. Change in Bank Capital ($\Delta ca_{i,t}$) is the absolute change from the year *t-1* to *t* of bank *i*'s equity-to-total assets ratio. In Column (1), the first-stage estimation is shown, using the three-quarter lagged average value of bank liquidity creation as the instrument to obtain the predicted value of bank liquidity creation. In Column (2), I use the predicted value of bank liquidity creation from the first-stage to estimate the relationship between bank liquidity creation and bank failure risk. The variable descriptions are in Appendix 2.2. Robust standard errors clustered by bank are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

2.6.4 Alternative measures of bank capital

To study the liquidity-risk sharing role of bank capital is a key element of this paper. In the main analysis, I use the ratio of equity capital to total assets (*ca*), as the measure of bank capital. To check if my main results are sensitive to the measure of bank capital, I re-run the regressions using regulatory capital ratios that are applied in terms of the Basel Accord. I use two risk-based capital ratios which are introduced by Basel I, i.e., the Tier 1 and Total risk-based capital ratios. The results based on these alternative capital ratios are shown in Table 2.9 and are qualitatively similar to the main results in Table 2.5. The coefficients of the interaction terms $catfat \times \Delta ca$ and $catnonfat \times \Delta ca$ are negative and statistically significant, suggesting that given the incremental increases in bank capital, no matter whether it is measured as the tier-1 capital divided by risk-weighted assets or total capital divided by the risk-weighted assets, bank liquidity creation negatively affects bank failure.

Table 2.9 Alternative measures of bank capital

Panel A: VARIABLES	(1) *bf1*	(2) *bf1*
catfat	-0.033***	
	(0.00)	
catfat*×Δ*ca	**-0.694*** **	
	(0.06)	
catnonfat		-0.016***
		(0.00)
catnonfat*×Δ*ca		**-0.991*** **
		(0.07)
Δ*ca*	-0.215***	-0.192***
	(0.02)	(0.02)
Bank-specific characteristics:		
ca	-0.466***	-0.447***
	(0.02)	(0.02)
aq	0.071**	0.071**
	(0.03)	(0.03)
mc	-0.001	0.001
	(0.00)	(0.00)
roe	-0.218***	-0.218***
	(0.01)	(0.01)
liq	-0.008	-0.009
	(0.01)	(0.00)
ltdrt	-0.002	-0.008***
	(0.00)	(0.00)
noniirt	0.000***	0.000***
	(0.00)	(0.00)
sd	0.004***	0.004***
	(0.00)	(0.00)
ristak	0.044***	0.035***
	(0.00)	(0.00)
commre	-0.000	-0.000
	(0.00)	(0.00)
lndep	0.000	0.000
	(0.00)	(0.00)
Macroeconomic characteristics:		
fedfunds	0.006	0.007
	(0.01)	(0.01)
spread	0.004	0.004
	(0.01)	(0.01)
lngdp	0.400*	0.403*
	(0.23)	(0.23)
lngpsave	0.028	0.023
	(0.04)	(0.04)
Local economic characteristics:		
hhi_dep	0.000	0.000
	(0.00)	(0.00)
lnpop	-0.001	-0.001
	(0.00)	(0.00)
sloos	0.000***	0.000***
	(0.00)	(0.00)
lnperinc	-0.012***	-0.012***
	(0.00)	(0.00)
lnemploy	0.002	0.002
	(0.00)	(0.00)
Constant	-3.845*	-2.726
	(2.20)	(2.08)
Year_quarter FE	Yes	Yes
Bank FE	Yes	Yes
State FE	Yes	Yes
Observations	288,435	288,435
R-squared	0.159	0.159

Panel B: VARIABLES	(1) *bf1*	(2) *bf1*
catfat	-0.033***	
	(0.00)	
catfat*×Δ*ca	**-0.727*** **	
	(0.06)	
catnonfat		-0.016***
		(0.00)
catnonfat*×Δ*ca		**-1.047*** **
		(0.07)
Δ*ca*	-0.220***	-0.194***
	(0.02)	(0.02)
Bank-specific characteristics:		
ca	-0.468***	-0.449***
	(0.02)	(0.02)
aq	0.071**	0.071**
	(0.03)	(0.03)
mc	-0.002	0.001
	(0.00)	(0.00)
roe	-0.218***	-0.218***
	(0.01)	(0.01)
liq	-0.008	-0.009
	(0.01)	(0.01)
ltdrt	-0.002	-0.008**
	(0.00)	(0.00)
noniirt	0.000***	0.000***
	(0.00)	(0.00)
sd	0.004***	0.004***
	(0.00)	(0.00)
ristak	0.045***	0.035***
	(0.00)	(0.00)
commre	-0.000	-0.000
	(0.00)	(0.00)
lndep	0.000	0.000
	(0.00)	(0.00)
Macroeconomic characteristics:		
fedfunds	0.006	0.007
	(0.01)	(0.01)
spread	0.004	0.004
	(0.01)	(0.01)
lngdp	0.401*	0.404*
	(0.23)	(0.23)
lngpsave	0.028	-0.022
	(0.04)	(0.04)
Local economic characteristics:		
hhi_dep	0.000	0.000
	(0.00)	(0.00)
lnpop	-0.001	-0.001
	(0.00)	(0.00)
sloos	0.000***	0.000***
	(0.00)	(0.00)
lnperinc	-0.012***	-0.012***
	(0.00)	(0.00)
lnemploy	0.002	0.002
	(0.00)	(0.00)
Constant	-3.850*	-3.829*
	(2.20)	(2.18)
Year_quarter FE	Yes	Yes
Bank FE	Yes	Yes
State FE	Yes	Yes
Observations	288,435	288,435
R-squared	0.159	0.159

Note: This table presents the results of multivariate OLS regression models in which bank capital (*ca*) is measured as the ratio of Tier-1 capital over risk-weighted assets (Panel A) and Total capital divided by risk-weighted assets (Panel B). Change in Bank Capital ($\Delta ca_{i,t}$) is the absolute change from the year *t-1* to *t* of bank *i*'s Tier 1 risk-based capital ratio and Total risk-based capital ratio. The dependent variable is *Bank Failure* (*bf1*), a dummy that equals one if a bank fails within the next 12 months after a specific financial report date and zero otherwise. *Bank Liquidity Creation* is proxied by BB measure (*catfat* and *catnonfat*). The variable descriptions are in Appendix 2.2. I report only specifications that include all the control variables and all fixed effects in this table. Robust standard errors clustered by bank are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

2.7 Conclusion

This paper empirically examines the role of bank capital in moderating the relationship between bank liquidity creation and bank failure. The main findings are the following. Firstly, without controlling for bank capital, liquidity creation is positively associated with bank failure risk. This is because liquidity creation increases the probability of higher losses due to fire sale prices when illiquid assets are sold to meet a sudden increase in customers' liquidity demands (Diamond and Dybvig, 1983; Diamond and Rajan, 2011; Allen and Santomero, 1997; Allen and Gale, 2004), which in turn can lead to the failure of banks. Secondly, once I control for bank capital, I have found a fairly robust and significant negative relationship between liquidity creation and bank failure risk. This can be explained by the liquidity-risk sharing function of bank capital. In other words, the liquidity risk can be mitigated through the bank capital channel. Specifically, banks that create more liquidity and are then exposed to higher liquidity risk may find it optimal to hold/maintain more capital as cushion to absorb the illiquidity risk stemming from bank liquidity creation. This would, in turn, reduce the probability of bank failure. Thirdly, the negative and significant effect of bank capital on the relationship between liquidity creation on bank failure is more prominent for small banks. This is not surprising, since access to external funds is more limited for small banks (Allen, Peristiani and Saunders, 1989). They have strong precautionary motive for holding more capital as a hedge against liquidity shocks and thus are less likely to fail. Finally, I also find that the effect of bank capital on the relationship between bank liquidity creation and bank failure risk is more pronounced during the recent financial crisis period. This implies that bank capital plays a critical role in alleviating liquidity risk from liquidity creation during the crisis period.

This study has important policy implications for policymakers and bank regulators as it provides novel insights for the design of prudential regulation and supervision of banks. Prudential regulation, in the form of liquidity or capital requirements, is designed to enhance the resilience of the banking system to shocks by requiring institutions to maintain prudent levels of liquidity and capital under a broad range of market conditions. The financial crisis of 2007-2009 has prompted the Basel Committee on Banking Supervision (BCBS) to introduce a new regulatory framework, known as Basel III, to strengthen the capital and liquidity risk management of banks. The findings in this paper show that capital and liquidity requirements cannot be separated. Policymakers should consider the liquidity-risk sharing function of bank capital as an integrated component of bank liquidity management and evaluate its effect on the relationship between liquidity creation and bank failure. Furthermore, the findings clearly indicate that one size does not fit all when it comes to capital and liquidity regulation. It appears that large banks may underestimate liquidity risk and maintain low capital ratios because of their "too-big-to-fail" positions. My findings indicate that stringent capital requirements should be imposed on large banks to induce them to raise capital and reduce the probability of failure. Beyond the scope of this paper, other interesting avenues remain open for further research. In particular, how does the Basel III liquidity requirement – liquidity coverage ratio (LCR) and the net stable funding ratio (NSFR), affect the relationship between bank liquidity creation and failure risk? How will liquidity management of banks affect the relationship between bank capital and the probability of default? What is the price of raising new capital as opposed to building reserves from profits?

Appendix 2.1 Liquidity classification of bank activities and construction of liquidity creation measures

In one of the ground-breaking papers in bank liquidity creation, Berger and Bouwman (2009) construct their liquidity creation measure using a three-step approach. In the first step, they classify all bank balance sheet and off-balance sheet activities as liquid, semi-liquid, or illiquid based on the ease, cost, and time it takes for customers to withdraw liquid funds from the bank, and the ease, cost and time it takes for a bank to dispose of its obligations to meet customers' demands. In the second step, they assign weights of either +1/2, 0, or -1/2 to all of the bank activities classified in the first step. The weights are based on the liquidity creation theory, according to which liquidity is created when banks transform illiquid assets into liquid liabilities and liquidity is destroyed when liquid assets are financed by illiquid liabilities or equity. Therefore, positive weights (+1/2) are applied to illiquid assets, liquid liabilities and illiquid off-balance sheet guarantees, while negative weights (-1/2) are applied to liquid assets, illiuqid liabilities, equity and liquid off-balance sheet guarantees. A weight of zero is applied to semi-liquid assets, semi-liquid liabilities and semi-liquid guarantees. In the third step, they combine the activities as classified and weighted in the first two steps to obtain liquidity creation measures. Note that liquidity creation measures used in this study (*catfat* and *catnonfat*) are based on category rather than maturity.

Assets	**Liquidity level**		
	Illiquid (weight=½)	Semiliquid (weight=0)	Liquid (weight=-½)
Commercial real estate loans (CRE)	√		
Loans to finance agricultural production	√		
Commercial and industrial loans (C&I)	√		
Other loans and lease financing receivables	√		
Other real estate owned (OREO)	√		
Customers' liability on bankers acceptances	√		
Investment in unconsolidated subsidiaries	√		
Intangible assets	√		
Premises	√		
Other assets	√		
Residential real estate loans (RRE)		√	
Consumer loans		√	
Loans to depository institutions		√	
Loans to state and local governments		√	
Loans to foreign governments		√	
Cash and due from other institutions			√
All securities			√
Trading assets			√
Fed funds sold			√
Liabilities and equity	**Liquidity level**		
	Liquid (weight=½)	Semiliquid (weight=0)	Illiquid (weight=-½)
Transaction deposits	√		
Saving deposits	√		
Overnight federal funds purchased	√		
Trading liabilities	√		
Time deposits		√	
Other borrowed money		√	
Bank's liability on bankers acceptances			
Subordinated debt			√
Other liabilities			√
Equity			√
Off-balance sheet guarantees and derivatives	**Liquidity level**		
	Illiquid (weight=½)	Semiliquid (weight=0)	Liquid (weight=-½)
Unused commitments	√		
Net standby letters of credit	√		
Commercial and similar letters of credit	√		
All other off-balance sheet liabilities	√		
Net credit derivatives		√	
Net securities lent		√	
Net participations acquired			√
Interest rate derivatives			√
Foreign exchange derivatives			√
Equity and commodity derivatives			√

Source: Berger and Bouwman (2009)

Appendix 2.2 Variable definitions

Variable	Definition
Panel A: Bank liquidity creation and bank failure risk variables	
catfat	Dollar amount of "*catfat*" liquidity creation normalized by gross total assets. The "*catfat*" measures the liquidity created on and off the balance sheet, following Berger and Bouwman (2009)
catnonfat	Dollar amount of "*catnonfat*" liquidity creation normalized by gross total asset. The "*catnonfat*" measures the liquidity created on the balance sheet, following Berger and Bouwman (2009)
bf	A binary performance variable is used to indicate whether a bank fails within the next one (*bf1*), two (*bf2*), three (*bf3*) and five (*bf5*) years after a specific financial report date. If failure occurs, it is flagged as "bad" and is assigned the binary value of one. Otherwise, it is flagged as "good" and is assigned the binary value of zero
Panel B: Bank-specific variables	
ca	The ratio of equity capital to total assets
aq	The ratio of all nonperforming loans (all loans 90 days past due plus all loans charged off) to total assets
mc	The cost-to-income ratio
roe	The ratio of net income to total equity
liq	The ratio of cash and balances due from depository institutions to total assets
ltdrt	The loans-to-deposits ratio
noniirt	The ratio of non-interest income to total income
sd	The standard deviation of a bank's return on assets over the previous twelve quarters
ristak	The bank's Basel I risk-weighted assets divided by total asset
commre	The commercial real estate loans divided by total loans
lndep	The natural logarithm of total bank deposits
Panel C: Macroeconomic variables	
fedfunds	The Federal funds rate
spread	The spread between 3-month US T-Bills and 10-year US Treasuries
lngdp	Natural logarithm of Gross Domestic Product
lngpsave	Natural logarithm of Gross Private Savings of all US households
crisisdummy	A dummy variable that equals one from the third quarter of 2007 to the fourth quarter of 2009 and zero otherwise
Panel D: Local market variables	
sloos	Net percentage of domestic banks reporting stronger demand for commercial and industrial loans
hhi_dep	Bank-level HHI of deposit concentration for the local markets in which the bank is operating. The local market is defined as the county in which bank headquarter is located
lnperinc	Natural logarithm of per capita personal income in a county
lnemploy	Natural logarithm of total employment in a county
lnpop	Natural logarithm of total population in a county

CHAPTER 3

TARP CAPITAL INFUSION, BANK LIQUIDITY HOLDINGS AND LIQUIDITY CREATION

3.1 Introduction

The financial turmoil that started in the summer of 2007 brought the U.S. financial system to the verge of collapse. In response to the worst economic downturn in the U.S. since the Great Depression, the Troubled Asset Relief Program (TARP), the largest government rescue program in U.S. history, was facilitated by the Emergency Economic Stabilization Act of 2008 (EESA) on October 3, 2008. The main objectives of the TARP were to restore the liquidity and stability of the financial system; to increase availability of credit to businesses and consumers; to prevent a systemic collapse of the economy; and to restore confidence in the nation's banking system. It entailed the purchasing of up to $700 billion of the troubled assets of banking institutions and direct injection of up to $250 billion of the TARP funds into qualifying financial institutions (QFIs)[16] under the Capital Purchase Program (CPP). It was the largest bank investment program to pursue the objective under TARP.

The aforementioned situation highlighted the importance of research about the risk of banks as core component of the financial system; determinants of bank bailouts; forms of bailouts; and the implication of such bailouts from different risk perspectives. As such existing literature were augmented by inter alia numerous empirical research

[16] Qualifying financial institutions (QFIs) included bank holding companies, financial holding companies, insured depository institutions, and savings and loan holding companies that were established and operating in the U.S. and that were not controlled by a foreign bank or company.

about the TARP, bank bailouts and the liquidity holding of banks in different circumstances.

Existing empirical literature relating to the TARP can be grouped into four areas. Firstly, a number of papers study the determinants of the TARP capital allocation and repayment (Duchin and Sosyura, 2012; Li, 2013; Blau, Brough and Thomas, 2013; Bayazitova and Shivdasani, 2012; Wilson and Wu, 2012; Wilson, 2013; Cadman, Carter and Lynch, 2012; Liu, Kolari, Tippens and Fraser, 2013; Taliaferro, 2009; Ng, Vasvari and Wittenberg-Moerman, 2016; Cornett, Li and Tehranian, 2013). Secondly, another main focus area of empirical literature is the stock market valuation effects of the TARP (Ng, Vasvari and Wittenberg-Moerman, 2016; Jordan, Rice, Sanchez and Wort, 2011; Elyasiani, Mester and Pagano, 2014; Kim, 2010; Farruggio, Michalak and Uhde, 2013; Bayazitova and Shivdasani, 2012; Veronesi and Zingales, 2010; Kim and Stock, 2012; Liu, Kolari, Tippens and Fraser, 2013; Norden, Roosenboom and Wang, 2011). Thirdly, the impact of the TARP on bank risk-taking and/or bank lending is investigated (Black and Hazelwood, 2013; Duchin and Sosyura, 2014; Taliaferro, 2009; Li, 2013; Contessi and Francis, 2011; Puddu and Waelchli, 2015; Wilson and Wu, 2010; Wilson, 2012). Finally, the literature explores the relation between the TARP investments and bank efficiency (Harris, Huerta and Ngo, 2013), stock market volatility (Huerta, Liston and Jackson, 2011; Nguyen and Enomoto, 2009), and bank competition (Koetter and Noth, 2012; Berger and Roman, 2015).

The literature on bank bailouts are diverse and growing (Giannetti and Simonov, 2013; Dam and Koetter, 2012; Gropp, Hakenes and Schnabel, 2011; Acharya, Drechsler and Schnabl, 2014). Rationales for government bailouts of troubled banks include financial contagion risks (Goodhart and Huang, 2005; Flannery, 2010); the fear of a systemic meltdown (Fischer, Hainz, Rocholl and Steffen, 2014), costly and inefficient liquidity provision by private agents (Gorton and Huang, 2002) and the risk of a bank run (Goldsmith-Pinkham and Yorulmazer, 2010). In particular, the recent financial crisis has generated a surge of theoretical and empirical research about bank recapitalization/capital infusion. For example, Philippon and Schnabl (2013) point out that for recapitalizations to be effective, bank bailouts have to be large enough to solve bank debt overhang problems. By comparing the U.S. crisis with the Japanese crisis, Hoshi and Kashyap (2010) derive eight lessons from Japan and evaluate the U.S. recapitalization policies in terms of the lessons. Furthermore, there is a growing concern among policymakers and academics about the long-run effects of bank bailouts. For example, Calderon and Schaeck (2012) found that competitive distortions resulting from rescue operations remain in place for up to five years following the rescue operations. Also Hryckiewicz (2012) shows that government interventions increase the risk-taking of bailed out institutions several years afterwards and destabilize banking sectors in the long-run.

The rich literature on bank liquidity holdings research differences in the liquidity holdings of banks in different circumstances. Banks hold liquid assets to self-insure against the occurrence of a liquidity shock. However, this is costly for banks, as liquid assets usually have lower returns than more productive illiquid or risky assets that they could instead invest in. Alternatively, banks may rationally choose to rely on liquidity from an interbank market (Bhattacharya and Gale, 1987; Allen, Carletti and Gale, 2009; Castiglionesi, Feriozzi, LÓRÁNth and Pelizzon, 2014) or central bank's liquidity support, such as a lender of last resort (LOLR) (Repullo, 2005; Goodhart and Huang, 2005; Acharya, Shin and Yorulmazer, 2011).

This paper augments three of the aforementioned areas of research (TARP, bailout of banks and bank liquidity holdings). The TARP-related literature entails extensive research, but does not address the impact of the TARP capital injection on bank liquidity. In this paper, I address whether higher government capital support in the form of the TARP leads to higher or lower levels of liquidity holdings by banks and stimulates bank liquidity creation. Considering the existing literature regarding the liquidity holdings of banks, this paper is closely related to that of Acharya, Shin and Yorulmazer (2011) who studied how bank liquidity is affected by regulatory intervention, aimed at resolving banking crises. They point out in their model that liquidity support to failed banks (or, in other words, bailouts) and unconditional liquidity support to surviving banks decrease the incentives of banks to hold liquidity. In contrast, conditional liquidity provision to surviving banks increases the incentives of banks to hold liquidity. This paper complements their research by empirically studying the effect of bailouts in the form of capital support (recapitalization) on bank liquidity holdings. In addition, this study complements their investigation about the effect of resolution policies on the *ex ante* liquidity positions of banks. This is done by examining the resulting effect of government bailouts on *ex post* bank liquidity positions.

Existing literature about bank liquidity creation differ about how capital affects liquidity creation. According to the "financial fragility-crowding out" hypothesis, capital has a negative effect on liquidity creation because a deposit contract would mitigate the hold-up problem of banks that cannot be resolved by bank capital (Diamond and Rajan, 2000, 2001) and a higher capital ratio may reduce liquidity creation through the crowding out of deposits (Gorton and Winton, 2017). In contrast, the "risk absorption" hypothesis, implies that there is a positive effect of capital on liquidity creation because capital helps to absorb the illiquidity risks associated with liquidity creation and expands the risk-bearing capacity of banks (e.g., Bhattacharya and Thakor, 1993; Allen and Santomero, 1997; Allen and Gale, 2004; Repullo, 2004; Von Thadden, 2004; Coval and Thakor, 2005). My empirical results support the "risk absorption" hypothesis of a positive effect of capital levels on liquidity creation. In the wake of the financial crisis, government assistance became an important issue. In particular, government intervention in the U.S. and Germany has received the most attention in the literature. However, to the best of my knowledge, there is no empirical work on the effect of the TARP capital injection, the largest government rescue program in U.S. history, on liquidity creation. In this regard, the paper closest to this study is that of Berger, Bouwman, Kick and Schaeck (2016). Using a banking sector dataset in Germany, they show that capital support does not affect liquidity creation, which differs from my results that the TARP capital support increases liquidity creation. The difference in the findings may be due to the following. Firstly, I focus on the TARP, the largest government rescue program in U.S. history that took place during the recent financial crisis period. Banks were encouraged to create more liquidity upon receiving the TARP because the explicit policy objective of the TARP was to restore the liquidity and stability of the financial system.[17] In contrast, capital

[17] The explicit goal of TARP is to increase bank lending, which is a key component of bank liquidity creation (Black and Hazelwood, 2013; Duchin and Sosyura, 2014; Berger, Bouwman, Kick and Schaeck, 2016).

support in their study covers both crisis and non-crisis periods from 1999 to 2009. During non-crisis period, the drive of banks for liquidity creation may be different. Secondly, in the U.S., government capital injections, targeted a large fraction of banks, were "voluntary" in the sense that banks could choose to apply for and accept the government injections. In this setting, a bank's approval for TARP implied that the regulators viewed it as sufficiently healthy and/or systemically important to receive government support (Duchin and Sosyura, 2014). Therefore, it is expected that these financially strong banks might have the ability to create more liquidity upon receiving TARP. In contrast, in Germany, capital injections were mandatory, targeted the weakest 7% of banks, and sent a strong negative signal that the bank was put on close watch by the regulators (Duchin and Sosyura, 2014). Hence, it is likely that these unhealthy banks may not have the ability to create liquidity upon receiving capital injection.

It is very important to compare the costs and benefits of government assistance programs during the crisis period (Calomiris and Khan, 2015). The primary contribution of this paper to the existing literature is that it provides additional evaluation of the effectiveness of the TARP program, and will be of particular importance to policymakers and supervisory authorities for assessing government-supported schemes and designing the most effective regulatory framework. Applying a difference-in-difference (DID) regression model on a sample of U.S. banks over the period 2003:Q1 to 2014:Q4, my findings support the previous empirical findings about the dominance of the "precautionary motive" and "strategic motive" of liquidity holdings in the banking literature.[18] As such, the findings provide strong evidence that the higher the government capital support is that banks receive, the lower the levels of their liquidity holdings are. Further, Berrospide (2013) found that more than one-fourth of the reduction in bank lending during the crisis was due to the precautionary motive. Thus, if government intervention through the infusion of capital into banks can decrease the incentives of banks to hold liquidity, then it may encourage lending

[18] "Precautionary motive" refers to the hoarding of liquidity by banks for self-insurance against unexpected demand deposit withdrawals and drawdowns of off-balance sheet loan commitments in higher uncertainty circumstances. "Strategic motive" refers to the hoarding of liquidity by banks to be able to take advantage of profitable options when they arise, for example to enable healthy banks to use their liquidity buffers to acquire failed banks and/or acquire assets at deep discounts in future. See Section 3.3 Literature review and hypotheses development for further discussion of "precautionary" and "strategic" motives.

activities of banks. This paper expands the bank lending literature by also considering it as an element of bank liquidity creation. Liquidity creation is a core function of banks to support the macro-economy. Banks create liquidity on the balance sheet by activities, such as converting illiquid assets to meet liquid liabilities (e.g., Bryant, 1980; Diamond and Dybvig, 1983). Banks also create liquidity off the balance sheet by activities, such as providing standby letters of credit and loan commitments to their customers (e.g., Holmström and Tirole, 1998; Kashyap, Rajan, and Stein, 2002; Thakor, 2005). In other words, banks create liquidity by holding illiquid assets (e.g., business loans and loan commitments) and provide liquid assets to the rest of the economy (e.g, cash and transaction deposits). Similarly, liquidity can be destroyed when banks use illiquid liabilities (e.g., subordinated debt) or equity to finance liquid assets (e.g., treasury securities) (Berger and Bouwman, 2009). Liquidity creation differs from liquidity holdings in that liquidity holdings weaken the ability of banks to create liquidity. For example, cash and marketable securities held by a bank decrease liquidity creation since holding cash/liquidity takes something liquid away from the public. The results in this paper show TARP capital infusion indeed enhances the liquidity creation of banks. I also test the robustness of the main findings by way of a number of checks, including (1) an alternative model specification; (2) different bank size classes; (3) an alternative bank liquidity ratio; and (4) different bank capital levels.

The remainder of this paper is organized as follows. Section 3.2 provides some details about the Capital Purchase Program (CPP). Section 3.3 contains the literature review and the hypotheses. Section 3.4 presents the data, variables, and sample construction, followed by the empirical methodology in Section 3.5 where the main results and the endogeneity concern are discussed. A series of related robustness checks are conducted in Section 3.6, followed by the conclusion in Section 3.7.

3.2 Background to CPP

The Capital Purchase Program (CPP) is the cornerstone of the TARP. On October 14, 2008, U.S. Treasury Secretary Henry Paulson announced a revision to the implementation of the TARP. It entailed the decision by Treasury to directly inject up to $250 billion of TARP funds into qualifying financial institutions (QFIs) under the CPP in order to improve the capital positions of banks and to encourage them to resume lending, thereby easing the tight credit market conditions. In exchange for the CPP capital, banks provided the Treasury with non-voting preferred stock, which paid quarterly dividends at an annual yield of 5% for the first five years and 9% thereafter, and ten-year life warrants to purchase common stock for an amount equal to 15% of the preferred equity infusion. This gave taxpayers the opportunity to benefit from the banks' future growth. The amount of the CPP capital that a QFI could apply for was restricted to between 1% and 3% of the QFI's risk-weighted assets or $25 billion, whichever was smaller.

Initiated in October 2008 and terminated in December 2009, the CPP invested $204.9 billion[19] with 707 financial institutions. The largest investment was $25 billion and the smallest was $301,000. Under the CPP, the first nine large banks[20] were forced to participate in the CPP due to their status as the largest financial institutions and did not follow the formal CPP evaluation process, whereas the other recipient banks participated voluntarily in the CPP. These banks followed the formal process and applied for the CPP funds from the U.S. Treasury. The Treasury established different application deadlines for different types of financial institutions. November 14, 2008, December 8, 2008, February 13, 2009, May 14, 2009, and November 11, 2009 were deadlines for public, private, S-corporations, mutual, and small community banks, respectively. To apply for the CPP funds, QFIs needed to submit two-page applications to their primary banking regulator: the Fed, FDIC, OCC or OTS. Bank holding companies were asked to submit their applications to both the Fed (their primary regulator) and the primary regulator of their largest subsidiary. If the initial application review by the banking regulator was successful, the application was forwarded to the Treasury, which made the final decision on the investment. The application process was kept confidential because regulators were concerned that depositors might interpret the non-award of TARP funds as a signal of poor health. Such interpretation

[19] Treasury initially committed $250 billion of TARP funding to the CPP, however, the amount was ultimately reduced to approximately $205 billion.
[20] The first eight banks that received CPP funds are Citigroup, Wells Fargo (including Wachovia), JPMorgan Chase, Bank of America (including Merrill Lynch), Goldman Sachs, Morgan Stanley, State Street, and Bank of New York Mellon.

could result in a bank run by depositors. They did not disclose which banks applied for the CPP funds, nor did they disclose which banks withdrew their applications or were rejected.

In addition, the CPP participants were subject to compensation restrictions. The initial restrictions were outlined at the program inception in October 2008.[21] In February, 2009, the American Recovery and Reinvestment Act (ARRA) became a law, amending the EESA and imposing more stringent executive compensation restrictions on the CPP recipients.[22] ARRA also allowed for early CPP repayment and withdrawal from the program without financial penalty. Thus, banks started repaying the CPP funds from March 2009, with the largest repayments in June and December 2009. The first CPP repayments were made on March 31, 2009 by four banks, which expressed concerns over the dividend and compensation restrictions associated with CPP infusions. In the following months, many other banks submitted applications to repay CPP infusions. According to the exit strategy announced on May 3, 2012, the Treasury focused on winding down the CPP. From inception of the program through September 30, 2014, the Treasury received $199.4 billion in CPP repayments and auction sales of preferred shares and subordinated debt, along with $12.1 billion in dividends and interest, and $14.9 billion of proceeds in excess of the original cost. It totalled $226.4 billion compared to the initially disbursed CPP funds of $204.9 billion. On September 30, 2014, $625 million in CPP gross investments remained outstanding (TARP Agency Financial Report, 2014). For simplicity, the term TARP is used henceforth to refer to CPP.

3.3 Literature review and hypotheses development

Gale and Yorulmazer (2013) developed a theoretical model of liquidity management to analyse the possibility of liquidity hoarding and its impact on

[21] For example, restrictions include limiting tax deductibility of compensation for senior executives to $500,000, requiring bonus claw-backs, and restricting golden parachute payments.
[22] ARRA further prohibited bonuses, retention awards, and incentive compensation other than long-term restricted stock awards that exceeded one-third of annual compensation.

efficiency. They found that the inefficiency of liquidity hoarding caused by incomplete markets always occurs with positive probability in a laisser-faire equilibrium. The central bank, the lender of last resort, can implement a constrained-efficient liquidity allocation to restore efficiency. In particular, they argue that if the central bank intervenes very aggressively, it can discourage bankers from holding liquidity. The TARP provides a natural testing ground to identify the relationship between government bailout and bank liquidity holdings in terms of the theoretical framework of Gale and Yorulmazer (2013). It is addressed in this paper by testing the effect of the TARP on bank liquidity holdings. My paper is related to that of Chang, Contessi and Francis (2014). They investigated the effect of the TARP on reserves and cash accumulation of banks. They found that banks, which received the TARP funds, accumulated less cash and reserves. This paper differs from that of Chang, Contessi and Francis (2014) in terms of the following: First, instead of examining the short term impact of TARP on cash holdings by using data of one quarter before the capital injection and six quarters after the capital injection in their paper, this paper investigates the long term effect of TARP on bank liquidity over a longer period of time. This long-term effect is important because the bank liquidity management strategy is most likely to be affected in the long run. Following Duchin and Sosyura (2014) and Berger and Roman (2017), I define the pre-TARP and post-TARP periods respectively as 2003:Q1-2008:Q4, and 2009:Q1-2014:Q4. Second, I hypothesize that if TARP can mitigate inefficient liquidity holdings of banks, it will spur bank lending and liquidity creation. This is not addressed in their paper. However, it is important since the stated policy objective of TARP was to increase lending by encouraging banks to deploy their liquidity, not to hoard it. In this paper, I also investigate whether TARP increases bank liquidity creation by weakening their precautionary and strategic motives for holding liquidity.

A well-functioning interbank market provides effective liquidity coinsurance by channelling liquidity between banks with liquidity surpluses and shortages (Allen, Carletti and Gale, 2009), which in turn minimizes holding of costly liquid assets by banks for which the returns are low. In fact, interbank market funding has, until the start of the global financial crises, been the primary source of liquidity for banks and one of the most liquid sources in the financial sector. However, there is clear evidence that the interbank lending market became disrupted since 2008. In the wake of the Lehman Brothers episode, the interbank market started showing sensitivity to borrower characteristics and particularly limited the lending to large banks with high levels of non-performing loans (Afonso, Kovner and Schoar, 2011). In this regard the interbank loans decreased from around USD 500 billion in early 2008 to about USD 100 billion in late 2011 (remaining about the same level to 2014).[23] During this interbank lending crunch, the spread between the London Interbank Offer Rate (LIBOR) and the Overnight Index Swap (OIS) rate, a primary indicator of stress in the banking sector (Sengupta and Tam, 2008; Thornton, 2009; Acharya and Skeie, 2011), increased to more than 350 basis points (bps) during October 2008, compared to its level of less than 10 bps in early 2007. The increased LIBOR-OIS spread, in addition to the loan limitations, reflected the increases in counterparty credit and liquidity risk (Christensen, Lopez and Rudebusch, 2013; Hesse and Frank, 2009; Michaud and Upper, 2008; Acharya and Skeie, 2011; McAndrews, Sarkar and Wang, 2008; Hesse, Frank and Hermosillo, 2008).

There is quite a strong evidence that the liquidity drying-up in the interbank market was triggered by the hoarding behaviour of financial institutions (e.g., Ashcraft, McAndrews and Skeie, 2011; Diamond and Rajan, 2011; Acharya and Skeie, 2011). The monthly series that show the holdings of cash (vault cash, cash items in process of collection, balances due from depository institutions and balances due from Federal Reserve Banks) by U.S. commercial banks are presented in Figure 3.1. As shown, even though the first wave of the subprime crisis started in August 2007, the cash holdings of U.S. commercial banks continued to stay stable right up to the failure of Lehman Brothers in early September 2008. After that, the cash holdings have increased dramatically. The incentives of banks to hoard liquid assets are driven by two reasons: precautionary motive and strategic motive (Gale and Yorulmazer, 2013). “Precautionary” motive refers to the hoarding of liquidity by banks for self-insurance purposes, such as insurance against counterparty risk and liquidity risk. As such, Acharya and Merrouche (2012) found that large U.K. settlement banks started hoarding cash to cover their transactional needs immediately following the freeze of the money market. Similarly, studies about the precautionary motive suggest that

[23] See http://research.stlouisfed.org/fred2/series/IBLACBW027NBOG

during the recent financial crisis, banks hoarded liquidity to protect themselves against future liquidity shocks, i.e. credit line drawdowns and unexpected demand deposit withdrawals (Cornett, McNutt, Strahan and Tehranian, 2011; Ashcraft, McAndrews and Skeie, 2011; de Haan and van den End, 2013; Mutu and Corovei, 2013) and in anticipation of future expected losses from security write-downs (Berrospide, 2013). "Strategic" motive refers to the holding of large liquidity positions by banks to speculate when profit opportunities exist like in the case of fire sales of assets from illiquid banks (Diamond and Rajan, 2011; Acharya, Shin and Yorulmazer, 2011; Brunnermeier and Pedersen, 2005). In other words, banks may hoard liquidity to be able to take advantage of profitable opportunities to acquire assets of stressed banks at a lower cost. Anecdotal evidence suggest how National City Bank, which eventually became Citibank, grew from a small treasury unit into one of the biggest commercial banks by building up liquidity and capital before the crises by benefiting from the difficulties of its competitors (Acharya, Shin and Yorulmazer, 2011).

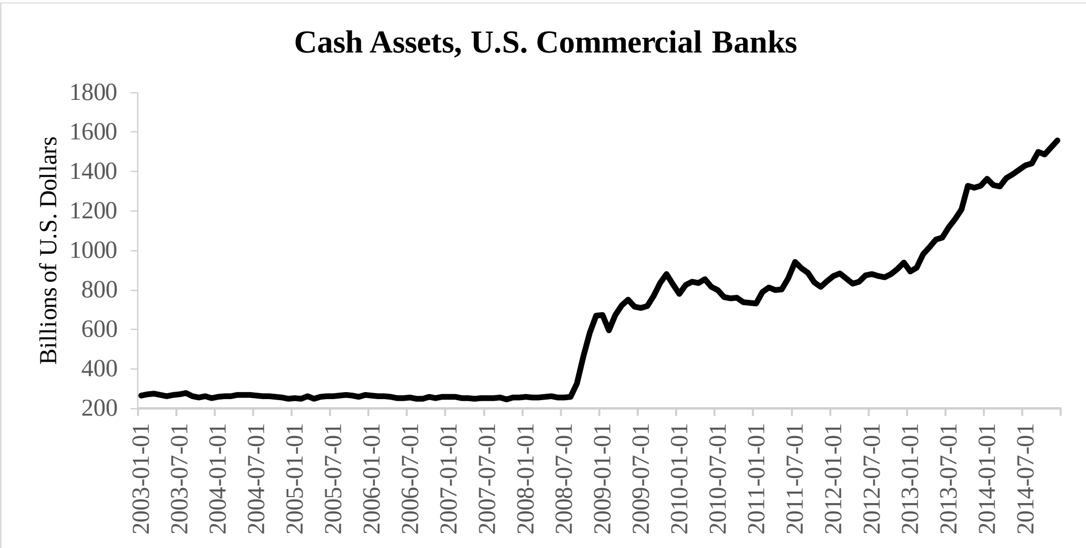

Figure 3.1 Monthly cash holdings of U.S. commercial banks (Source: Federal Reserve H8)

There are two basic theoretical motivations for my work. Firstly, Castiglionesi, Feriozzi, LÓRÁNth and Pelizzon (2014) explain that banks enter the interbank market to hedge away bank-specific risk. However, when the interbank market stops to provide this function (as it did during the financial crisis), banks have two alternatives. One is issuing capital, which they argue is costly, and the other is liquidity hoarding. This theory predicts that government support, if intended to help strengthen banks through capitalization, can discourage banks from hoarding liquidity and therefore reduce liquid asset holdings by banks. Thus, I predict that government capital support may provide banks with the assurance of safety and thereby reduce precautionary liquidity hoarding incentives (i.e., banks would not have to hold as much liquidity for survival). Secondly, Acharya, Gromb and Yorulmazer (2012) relates liquidity hoarding to so-called "predatory behavior" of liquidity-surplus banks, aimed at the exploitation of urgent liquidity needs of other banks. They found that banks with liquidity surplus have an incentive to hoard liquid assets and strategically underprovide liquidity to banks with liquidity deficit so as to benefit from the fire sale of assets from illiquid banks in desperate need of liquid funds, which results in inefficient liquidity transfers. Hence, I predict that government capital support may ameliorate this inefficiency by standing ready to inject liquidity to (deficit) banks as this would lower the chance of forced future fire sales of assets by distressed banks and thereby mitigate strategic liquidity hoarding incentives of (surplus) banks.

Based on the aforementioned predictions/expectations, I formulate my first hypothesis to test the relationship between TARP capital support and bank liquidity holdings:

Hypothesis: higher government capital support is associated with lower levels of liquidity holdings by banks.

It is noteworthy that when banks hold higher levels of liquidity, then it constrains their lending and liquidity creation. Gale and Yorulmazer (2013) model both the precautionary and the strategic motives for holding cash and show that banks may hoard liquidity and lend less than the maximum possible amount. Lending is a key component of asset-side liquidity creation and therefore liquidity creation is also reduced. Berger and Sedunov (2017) also argue that liquidity hoarding takes something liquid away from the public and discourages banks from creating liquidity. Perhaps more importantly, liquidity creation is viewed as the best available measure of total bank output (Berger and Sedunov, 2017). Thus, I expand upon the bank lending channel literature by broadening the focus to bank liquidity creation – which includes much more than lending (Berger and Bouwman, 2017). In particular, I hypothesize that if government capital support can alleviate liquidity hoarding behaviour of banks, it may stimulate bank liquidity creation. This leads to the following sub-hypothesis:

Sub-hypothesis: higher government capital support is associated with higher levels of bank liquidity creation.

3.4 Data collection, sample construction and measurement of variables

3.4.1 Bank sample and TARP data

The dataset of this study focuses on the CPP, bank initiative program of TARP. A quarterly panel data set, spanning from the first quarter of 2003 to the fourth quarter of 2014, was compiled. The data used in this paper are from multiple sources.

Data on TARP is publicly available on the website of the U.S. Treasury. The Treasury's TARP Transaction Report includes the identity and location of the institution, the date the institution received TARP funds, and the amount of the funds received. Due to concerns that investors may interpret the non-award of TARP capital as a negative signal that may trigger bank runs on such applicants, the TARP program did not publicly disclose identities of unsuccessful applicants. Initiated in October 2008 and terminated in December 2009, TARP invested $204.9 billion in 707 financial institutions – 31 financial institutions received TARP capital injection twice and 676 financial institutions received once-off TARP funds.

The bank sample was retrieved from the Statistics on Depository Institutions (SDI) database, maintained by the Federal Deposit Insurance Corporation (FDIC), available at https://www5.fdic.gov/sdi/download_large_list_outside.asp. The SDI repository includes all FDIC-insured institutions and it contains detailed on-and off-balance-sheet information for all banks.[24] Bank data retrieved from the FDIC are merged with the TARP bank data. The initial TARP dataset consists of 738 TARP bank observations. Then, another 20 bank observations in the TARP Transaction Report are excluded because, due to a lack of specific TARP and/or SDI identity number, they cannot be matched with the banks in the SDI dataset. As a last step, two TARP amounts received by the same BHC and independent banks are combined (31 bank observations), and extreme observations are winsorized at the top and bottom 1%. Using this procedure, I have 599 BHC observations and 88 independent bank observations.

3.4.2 Variables

3.4.2.1 Dependent variables

Dependent variables used to test hypothesis and sub-hypothesis are bank liquidity holdings and bank liquidity creation, respectively. Following Chang, Contessi and Francis (2014), bank liquidity holding (*liqhod)* is defined as the sum of all cash and balances due from other financial institutions scaled by total assets. In the robustness test, liquidity holding (*liqhodr)* is measured as the sum of all cash and balances due from other financial institutions, fed funds sold less fed funds bought, and securities purchased under resale agreements less securities sold under repurchase agreements, and available-for-sale securities, scaled by total assets. In this study, Berger and Bouwman's (2009) liquidity creation measures (e.g., *catfat_gta* and *catnonfat_gta*) are used as a proxy for bank liquidity creation (hereafter referred to as BB measure).

[24] Depending on their bank holding company (BHC) status, there are three types of banks in my dataset, i.e., multibank holding company members, one-bank holding company members and independent banks. All applications in the case of subsidiaries were conducted via the BHCs. In the case of multibank holding company members, I assume that TARP funds are equally distributed across their subsidiaries.

3.4.2.2 Bank characteristics

The reasons for applying (or not applying) for TARP assistance by banks and the criteria used for approving applications are not revealed. However, previous studies provide strong evidence that the criteria *de facto* used by the respective regulators of applicant banks and by the U.S. Treasury to assess the applications for TARP funds rely on the so-called CAMELS[25] internal supervisory rating system (Duchin and Sosyura 2012, 2014; Li, 2013). In particular, the following control variables related to bank liquidity holdings are selected from the CAMELS rating system: the ratio of equity capital to total assets as a proxy of capital adequacy (*ca*); the ratio of all nonperforming loans to total assets as a proxy of asset quality (*aq*); the ratio of net income to total equity as a proxy of earnings (*roe*).[26] I control for bank holding company (*bhc*) status because the same BHC may serve as internal capital market to provide capital/liquidity to its different subsidiaries (Houston and James, 1998; Berger and Bouwman, 2009). With respect to the effect of TARP on bank liquidity creation, I also control for liquidity risk, measured as the ratio of unused loan commitments to total loans (*ucrt*) (Cornett, McNutt, Strahan and Tehranian, 2011) and bank risk taking (*ristak*), measured as the bank's Basel I risk-weighted assets divided by total assets (Berger and Bouwman, 2013).

3.4.2.3 Political and regulatory connection

Political connection or engagement plays an important role in the allocation of TARP funds (Duchin and Sosyura, 2012, 2014; Li, 2013; Blau, Brough and Thomas, 2013). They show that politically connected banks are more likely to receive TARP funds. In contrast, Bayazitova and Shivdasani (2012) found no evidence that political connection interfere with the TARP process. This study employs the same set of variables as Li (2013) to measure political influence.[27] The first variable (*Local FIRE Donation*) is the campaign contribution from local finance, insurance, and real estate

[25] Each acronym of CAMELS stands for capital adequacy; asset quality; management; earnings; liquidity; and sensitivity to market risk.
[26] Liquidity is excluded from this category of proxies since it is specified as the dependent variable in this study.
[27] I am grateful for Lei Li for offering this data.

(FIRE) industries as a percentage of total contribution received by a local political representative in the 2007-2008 election cycle. The larger the contribution percentage the more dependent representatives may be on local FIRE support for campaigns. The representatives may tend to reimburse FIRE industries by trying to assist them in their ventures to maintain their future support. The second variable (*Subcommittee on FICC*) takes the value of one if a representative serves on the Subcommittee on Financial Institutions and Consumer Credit, which supervises all federal banking regulators, and zero otherwise. The idea is that a representative would be more effective in influencing federal banking regulators if he/she serves on this subcommittee. The third variable (*Democrat*) takes the value of one if a representative was a member of the Democratic Party and zero otherwise since the Republican free-market ideology was considered to be generally more opposed to government bailouts of private firms. The final variable (*Fed Director*) takes the value of one if an executive of the bank served as a director of a branch of the Fed and zero otherwise since a bank with some Fed-connection might have been treated more favourably in the Fed's evaluation process.

3.4.2.4 Macroeconomic and local economic conditions

The status of the local economy is a major consideration in approving TARP applications (Li, 2013). More specifically, Bayazitova and Shivdasani (2012) point out that banks in severely affected regions may have had stronger incentives to apply for TARP funds, and regulators may have given these banks preferential treatment. Macroeconomic conditions also affect bank liquidity. Bank liquidity is countercyclical, that is, lower during economic upturns and higher when recessions approach (Acharya, Shin and Yorulmazer, 2011). The Federal funds rate (*fedfunds*) is the prevalent measure of monetary policy in empirical work (Campello, 2002; Chatterjee, 2015), thus this paper also uses the Federal funds rate as a proxy for the monetary policy, for which the data is obtained from the Federal Reserve Bank's website. Moreover, this study employs "yield spread" (*spread*), measured as the difference between long-term interest rates (10 year Treasury yield) and short-term interest rates (3 month Treasury yield), as a predictor of future real economic activity, for which the data is obtained from Federal Reserve Bank of New York. Following Imbierowicz and Rauch (2014), this study employs the natural logarithm of Gross Domestic Product (*lngdp*) and Gross

Private Savings (*lngpsave*) as macro controls, which are sourced from the St. Louis Federal Reserve "FRED" public database. In addition, county-level economic and demographic data (e.g., per capita personal income (*lnperinc*), total employment (*lnemploy*) and total population (*lnpop*)) are sourced from the Bureau of Economic Analysis (BEA). The Herfindahl-Hirschman Index (*hhi_dep*) is used to measure the level of competition for deposits among banks in local markets (Tran, Lin and Nguyen, 2016). Finally, I control for the recent financial crisis period, proxied by *crisisdummy*. This variable has a value of one from the third quarter of 2007 to the fourth quarter of 2009, and zero otherwise. The definitions and abbreviations used for the main variables are contained in Appendix 3.1 and descriptive statistics of the variables are provided in Table 3.1.

Table 3.1 Descriptive statistics

Panel A: Summary statistics of full sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	N	mean	sd	min	p25	p50	p75	max
liqhod	269,094	0.066	0.062	0.008	0.027	0.043	0.081	0.340
liqhodr	269,094	0.292	0.153	0.037	0.177	0.267	0.384	0.734
catfat_gta	269,094	0.307	0.177	-0.158	0.192	0.317	0.430	0.713
catnonfat_gta	269,094	0.251	0.154	-0.178	0.154	0.265	0.361	0.567
lc_obs_gta	269,094	0.055	0.039	0.001	0.027	0.046	0.073	0.207
taln	269,094	0.635	0.154	0.196	0.540	0.657	0.750	0.909
crln	269,094	0.095	0.066	0.004	0.048	0.080	0.124	0.345
rtln	269,094	0.043	0.041	0.000	0.014	0.031	0.057	0.223
TARP dummy	269,094	0.105	0.306	0	0	0	0	1
TARP amount	269,094	1.713	5.026	0	0	0	0	18.47
ca	269,094	0.108	0.035	0.049	0.086	0.100	0.120	0.271
aq	269,094	0.003	0.005	-0.001	0.000	0.001	0.004	0.030
roe	269,094	0.047	0.077	-0.362	0.021	0.046	0.083	0.228
bhc	269,094	0.841	0.366	0	1	1	1	1
fedfunds	269,094	1.537	1.864	0.070	0.120	0.190	2.940	5.260
spread	269,094	2.051	1.131	-0.512	1.529	2.249	2.875	3.578
lngdp	269,094	9.589	0.112	9.339	9.532	9.593	9.679	9.786
lngpsave	269,094	7.973	0.180	7.702	7.803	7.997	8.137	8.230
lnperinc	268,995	10.45	0.262	9.900	10.27	10.43	10.61	11.24
lnemploy	268,995	10.62	1.933	7.333	9.136	10.13	12.01	15.50
lnpop	268,995	11.22	1.828	7.834	9.886	10.78	12.54	16.09
crisisdummy	269,094	0.224	0.417	0	0	0	0	1
hhi_dep	269,094	-0.978	0.783	-3.592	-1.360	-0.896	-0.474	0
Feddirector	269,094	0.014	0.116	0	0	0	0	1
SubcommonFI	269,094	0.070	0.255	0	0	0	0	1
LocalFIREdonation	268,060	0.021	0.022	0	0.005	0.016	0.030	0.131
Dem	269,094	0.055	0.228	0	0	0	0	1

Panel B: Summary statistics of TARP and Non-TARP banks

	(1)	(2)	(3)
	TARP banks	Non-TARP banks	Difference in means
liqhod	0.054	0.067	0.013***
liqhodr	0.234	0.299	0.065***
catfat_gta	0.409	0.295	-0.114***
catnonfat_gta	0.325	0.242	-0.083***
lc_obs_gta	0.080	0.052	-0.028***
ca	0.103	0.109	0.006***
aq	0.004	0.003	-0.001***
roe	0.034	0.048	0.014***
no. of bank-quarter observations	28,159	240,935	-

Note: This table reports statistics that describe the sample. Panel A shows the summary statistics of key variables. Panel B reports the difference-in-means estimates to compare characteristics of TARP banks and non-TARP banks. See Appendix 3.1 for variable definitions. *, **, and *** denote 10%, 5%, and 1% significance level for the difference between TARP and non-TARP banks, respectively.

Panel A of Table 3.1 shows that the average bank liquidity holdings (*liqhod* and *liqhodr*) are 0.066 and 0.292, respectively. The mean value of bank liquidity creation (*catfat_gta* and *catnonfat_gta*) is 0.307 and 0.251, respectively. The mean value of capital adequacy (*ca*) and asset quality (*aq*) suggests that the sample banks have strong capital positions and high quality assets.

Summary statistics of TARP and non-TARP banks are presented in Panel B of Table 3.1. I compare the average bank liquidity holdings and liquidity creation between TARP banks and non-TARP banks.[28] Consistent with my hypotheses, the univariate tests in Panel B of Table 3.1 show that TARP banks hold lower levels of liquidity and create more liquidity than non-TARP banks. For example, the mean *liqhod* for TARP banks is 0.054 but is 0.067 for non-TARP banks, and the difference (0.013) is statistically significant at the 1% level of significance. The mean *catfat_gta* for TARP banks is 0.409 but is 0.295 for non-TARP banks, and the difference (-0.114) is statistically significant at the 1% level of significance. The preliminary results confirm my hypotheses that the TARP capital infusion can reduce bank liquidity holdings and thereby stimulate bank liquidity creation. Consistent with the findings of Li's (2013) paper, Panel B also shows that the non-TARP banks, on average, are better capitalized, have less troubled assets and earn higher return on equity than TARP banks. A two tailed t-test for the difference between the two groups yields a *p*-value less than 0.001.

3.5 Empirical methodology and main results

3.5.1 Econometric model

Following Duchin and Sosyura (2014), and Berger and Roman (2017), I use a difference-in-difference (DID) regression model to examine the effects of government capital support (TARP) on the liquidity holdings of banks, where the first difference is from before to after the TARP, and the second difference is between TARP recipients and non-TARP recipients. A DID estimator allows the comparison of banks that received the TARP funds (a treatment group) with a set of banks that did not

[28] In the remainder of this paper, TARP and non-TARP banks refer to the banks that received the TARP assistance and did not receive the TARP assistance, respectively.

receive any TARP funds (a control group) before and after TARP funding (treatment) was provided. An advantage of this empirical approach is that the DID estimator can account for omitted variables that affect treated and untreated groups alike by analysing the group differences at different times (Berger and Roman, 2017).

The DID regression model, applied over the sample period of 2003:Q1 to 2014:Q4, is specified as follows:

$$\begin{aligned} Y_{i,t} \\ &= \beta_0 + \beta_1 TARP\ Recipient_{i,t} + \beta_2\, Post\ TARP_{i,t} + \beta_3\, Post\ TARP_{i,t} \\ &\times\ TARP\ Recipient_{i,t} + \beta_4\, X_{i,t} + \Sigma Time\ and\ Bank\ Fixed\ Effects + \varepsilon_{i,t} \end{aligned} \tag{1}$$

The dependent variable $Y_{i,t}$ denotes the liquidity level of bank *i* during time *t*, defined as the sum of all cash and balances due from other financial institutions, scaled by total assets. The independent variables related to the TARP include the indicators $TARP\ Recipient_{i,t}$ (which equals one for banks that were TARP recipients and zero for banks that were not TARP recipients), $Post\ TARP_{i,t}$ (which equals one in 2009:Q1 to 2014:Q4, the period after the TARP program initiation and zero otherwise), and their interaction term $Post\ TARP_{i,t} \times TARP\ Recipient_{i,t}$ which is the DID term and captures any shift of bank liquidity holdings specific to TARP recipients induced by the implementation of the TARP. The vector of control variables $X_{i,t}$ contains determinants of bank liquidity holdings as identified in the literature, i.e. bank characteristics, macroeconomic and local economic conditions, which were explained in the Section 3.4.2, and $\varepsilon_{i,t}$ represents a white noise error term. I include time fixed effects to control for average differences in bank liquidity holdings across years and quarters that are not captured by the other exogenous variables such as business cycles, and to reduce serial correlation problems. I also include bank fixed effects to account for average differences over time across banks that are not captured by the other exogenous variables such as differences in business lines, and to reduce correlations across error terms. The main variable of interest is the interaction term $Post\ TARP_{i,t} \times TARP\ Recipient_{i,t}$, which shows how the marginal effect of the TARP on bank liquidity holdings of the TARP recipients relative to non-TARP recipients. Hence, a negative coefficient of interest β_3 is expected, suggesting that government bailouts would reduce liquid asset holdings by banks.

3.5.2 Empirical results

Table 3.2 presents the DID estimation results from my baseline specification on the relationship between TARP and bank liquidity holdings. According to Hausman (1978) specification test results (Chi-squared=261.15 and *p*-value=0.000), fixed effects estimation is recommended over random effects estimation for the sample.

Overall, the results in Table 3.2 show that the coefficient on the DID term, *Post TARP×TARP Recipient*, is always negative and statistically significant across all specifications, indicating that capital funds received by banks are followed by decreases in bank liquidity holdings. This finding supports my hypothesis that the higher government capital support is for banks, the lower the level of liquidity holdings are that these banks maintain afterwards. The magnitude can be quantified by the coefficient of the *Post TARP×TARP Recipient*, and I find very similar magnitudes across all models. For example, the Column (4) of Table 3.2 shows that the DID term coefficient (*Post TARP×TARP Recipient* coefficient of -0.011) is very similar to those reported in Column (1)-(3). All in all, I find that a 10% increase in the DID term results in a 0.11% reduction in bank liquidity holdings.

Turning to the control variables, I find that the coefficients of these variables largely have the predicted signs. For example, capital may negatively or positively affect bank liquidity creation (Berger and Bouwman, 2009). Along the same line, I find the evidence that capital cushion (*ca*) have positive or negative effect on liquidity buffers of banks. I also find that large proportions of non-performing assets (*aq*) may deplete the liquidity buffers of banks and there is a trade-off between liquidity buffers and profitability (*roe*). As expected, the variable bank holding company (*bhc*) is negatively related to liquidity holdings, suggesting that the same *bhc* may serve as internal capital market providing capital/liquidity to its different subsidiaries and thereby experience decreases in liquidity holdings. Finally, I find the mixed evidence on the effect of macroeconomic and local economic conditions on bank liquidity holdings. On the one hand, economic conditions may be related negatively to liquidity holdings because favourable economic conditions may unlock banks' precautionary and strategic motives of holding liquidity. On the other hand, economic conditions may be related positively to liquidity holdings because banks may have adequate liquidity buffer in good economic conditions.

Table 3.2 The effect of TARP on bank liquidity holdings: DID estimation results

VARIABLES	Model (1) *liqhod*	Model (2) *liqhod*	Model (3) *liqhod*	Model (4) *liqhod*
Post TARP × TARP Recipient	**-0.010*****	**-0.010*****	**-0.011*****	**-0.011*****
	(0.00)	(0.00)	(0.00)	(0.00)
TARP Recipient	-0.009***	-0.009***		
	(0.00)	(0.00)		
Post TARP	0.021***		0.020***	
	(0.00)		(0.00)	
ca	0.030***	0.029***	-0.133***	-0.132***
	(0.00)	(0.00)	(0.01)	(0.01)
aq	-0.334***	-0.437***	-0.273***	-0.396***
	(0.02)	(0.03)	(0.04)	(0.05)
roe	-0.071***	-0.082***	-0.063***	-0.077***
	(0.00)	(0.00)	(0.00)	(0.00)
bhc	-0.010***	-0.010***	-0.007***	-0.007***
	(0.00)	(0.00)	(0.00)	(0.00)
fedfunds	-0.009***	0.001	-0.009***	0.159***
	(0.00)	(726.40)	(0.00)	(0.05)
spread	-0.007***	0.028	-0.007***	0.091***
	(0.00)	(300.04)	(0.00)	(0.02)
lngdp	0.051***	0.696	0.063***	1.813***
	(0.00)	(5,344.17)	(0.01)	(0.31)
lngpsave	-0.023***	-0.515	-0.021***	-1.088***
	(0.00)	(2,844.51)	(0.00)	(0.14)
lnperinc	0.002**	0.002**	-0.014***	-0.014***
	(0.00)	(0.00)	(0.00)	(0.01)
lnemploy	0.000	0.000	0.006	0.007
	(0.00)	(0.00)	(0.01)	(0.01)
lnpop	0.000	-0.000	-0.006	-0.007
	(0.00)	(0.00)	(0.01)	(0.01)
crisisdummy	-0.016***	0.026	-0.015***	0.092***
	(0.00)	(318.24)	(0.00)	(0.02)
hhi_dep	-0.004***	-0.004***	-0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-0.237***	-2.568	-0.175***	-8.766***
	(0.02)	(29,684.66)	(0.03)	(1.88)
Year_quarter FE	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes
Observations	268,995	268,995	268,995	268,995
R-squared	0.153	0.160	0.231	0.242

Note: This table reports estimates from difference-in-difference (DID) regression analysing Eq. (1) for the impact of TARP on bank liquidity holdings. *TARP Recipient* takes the value of one if a bank is TARP recipient and zero otherwise. *Post TARP* is a dummy equal to one in 2009-2014, the period after TARP program initiation and zero otherwise. The variable descriptions are in Appendix 3.1. Model (2)-(4) report the results of OLS regressions, which include different Fixed Effects (FE) estimations (Year_quarter FE and Bank FE). TARP Recipient term is absorbed in individual fixed effects. Post TARP term is subsumed in time fixed effects. Heteroskedasticity robust standard errors in brackets below each coefficient estimate. *, **, and *** denote significance at 10%, 5% and 1% level, respectively.

3.5.3 Concerns of endogeneity

3.5.3.1 Erickson-Whited high-order cumulant estimators

To allow for the possibility that a TARP recipient is endogenous in Eq. (1), I apply the Erickson-Whited high-order cumulant estimation method to Eq. (1). Erickson, Jiang and Whited (2014) view endogeneity as an errors-in-variables problem and propose a procedure called XTEWreg to estimate a classical linear errors-in-variables model with arbitrarily many mismeasured regressors and perfectly measured regressors on panel data. Note that unlike the standard instrumental variable approach, where I need to find a third variable outside the system (or equation) as instrument, this approach uses information in the higher order cumulants/moments of the observable variables to identify the regression coefficient. The cumulant estimators are asymptotically equivalent to the moment estimators, but they have closed form solutions, so there are no computational difficulties. The model is specified as follows:

$$Y_{i,t} = X_{i,t} \times b + Z_{,t} \times a + u_{i,t}$$

$$x_{i,t} = X_{i,t} + v_{i,t} \tag{2}$$

where in Eq. (2), $Y_{i.t}$ is the dependent variable, $X_{i,t}$ is a vector of unobservable mismeasured regressors, $Z_{i,t}$ is a vector of perfectly measured regressors, $u_{i,t}$ is the regression disturbance, $x_{i,t}$ is the proxy for $X_{i,t}$, and $v_{i,t}$ represents the measurement errors. Subscripts *i* and *t* denote bank and period, respectively.

As shown in Column (1) of Table 3.3, there is still a negative and statistically significant relationship between TARP and bank liquidity holdings. The coefficient of the DID term, *Post TARP×TARP Recipient*, is -0.262, suggesting that a 10% increase in the DID term decreases bank liquidity holdings by 2.62%. The magnitude of the Erickson-Whited high-order cumulant estimation is much larger than that reported in the OLS specification.

3.5.3.2 Two-part model

The empirical findings with the DID model may be impacted by the fact that the TARP capital injections were not randomly assigned to banks. The non-randomness of the TARP allocation may give rise to a sample selection bias problem (Heckman, 1979). Under the TARP, banks may decide whether to apply for the TARP funds. The U.S. Treasury may choose whether to approve or disapprove the application, and once approved, banks may decide whether to accept or reject the TARP funds. Therefore, the impact of TARP capital injections on liquidity can only be observed for those banks that received the funds. Furthermore, unobservable variables, such as the "precautionary" and "strategic" motive of banks for holding liquidity, may affect the levels of bank liquidity irrespective of whether banks applied for assistance with the capital injection program or not. Standard regressions that ignore these issues may yield inconsistent coefficients because of the endogeneity problem arising from these issues. To address this potential selection bias caused by the non-random TARP funding (i.e. banks that received TARP funds were those that applied) and the endogeneity problem induced by the "precautionary" and "strategic" motive for liquidity holdings, a two-part model is employed.

As the name suggests, the two-part model consists of two parts. The first part models the probability of receiving TARP funds using a logit regression model for a binary outcome. The first part equation is:

$$TARP_i = \begin{cases} 1, & if \;\; \beta_0 + \beta'_{BC}X_{BC} + \beta'_{MLE}X_{MLE} + \beta'_{PR}X_{PR} + u_{1i} > 0 \\ 0, & otherwise \end{cases} \qquad (3)$$

where Eq. (3) is the logit model of the TARP dummy. TARP equals 1 if bank i is a TARP recipient and 0 otherwise; X_{BC} consists of bank characteristics; X_{MLE} controls for macroeconomic and local economic conditions; and X_{PR} includes political and regulatory connection variables.

The equation used in the second part models the distribution of the TARP amount to be received if applied for and if approved by using an OLS regression framework for a continuous outcome. The variables that are used for the specification of the first part are also used for the specification of the second part. The second part equation is:

$$TARP\ amount_i = \beta_0 + \beta'_{BC}X_{BC} + \beta'_{MLE}X_{MLE} + \beta'_{PR}X_{PR} + u_{2i} \tag{4}$$

The main equation to examine the effect of TARP on bank liquidity holdings based on the dollar amount of the capital infusion is:

$$Y_{i,t} = \beta_0 + \beta_1 TARP\ amount_{i,t} + \beta'_{BC}X_{BC} + \beta'_{MLE}X_{MLE} + \beta_2 Residual + u_{3i} \tag{5}$$

where in Eq. (5), the predicted residual value, "*Residual*", estimated after the two-part model, is added as an additional regressor in the main estimation. The output from the equation model above includes the naive error term, which assumes that there is no error in the generation of the "*Residual*" in the two-stage model. Bootstrapping is applied to deal with the fact that the "*Residual*" is a "generated" regressor (i.e., with estimation errors) that influences the computation of the standard error of the regression coefficient in the main estimation (1,000 bootstrap replications are performed). The dependent variable $Y_{i,t}$ denotes the liquidity level of bank *i* during time *t*, defined as the sum of all cash and balances due from other financial institutions, scaled by total assets. The main variable of interest is the $TARP\ amount_{i,t}$, expressed as the natural log of the amount of the TARP funds received by bank *i* during time *t*. X_{BC} consists of bank characteristics. X_{MLE} controls for macroeconomic and local economic conditions. Note that although political and regulatory connection variables (X_{PR}) may affect the probability and the amount of receiving TARP funds, it is unlikely that they will affect the banks' decision to hold liquidity. Therefore, these variables are included in two-part model but not in the main estimation. It is expected that a negative coefficient of interest β_1 will apply, suggesting that government bailouts will reduce high levels of inefficient liquid asset holdings by banks.

The statistically significant results of the two-part model that are contained in Table 3.3 reinforce the DID model findings. Column (4) of Table 3.3 shows that the TARP amount is significant negatively related to bank liquidity holdings, indicating that government capital support can reduce bank liquidity holdings. The coefficient of the TARP amount variable is substantially smaller than that of the DID term but it is still highly statistically significant. The coefficient for the TARP amount variable is -0.001, suggesting that one standard deviation increase in the TARP amount is associated with a 0.08 standard deviation decrease in bank liquidity holdings ($-0.001 \times 5.026/0.062$). This finding provides direct support for my hypothesis that higher government capital support is associated with lower levels of liquidity holdings by banks. The results on the effects of political variables on the probability and amount of receiving TARP funds are mixed. As the results in Column (2) and (3) show, I find that *Feddirector* has a positive and significant relationship with the probability and amount of TARP funds received by banks, whilst there is a negative and significant relationship between *LocalFIREdonation* and TARP funds. I also find that *SubcommonFI* has a significant positive relationship with the probability of receiving TARP funds whereas it is significantly negative related to the amount of TARP funds received. Finally, *Dem* has significant negative effect on the probability of receiving TARP funds whilst it has insignificant effect on the TARP amount received.

Table 3.3 The effect of TARP on bank liquidity holdings: controlling for endogeneity

	DID combined with Erickson-Whited high-order cumulant estimators	Two part model		OLS regression
	(1)	(2)	(3)	(4)
VARIABLES	*DV=Bank Liquidity Holdings (liqhod)*	logit	regress	*DV=Bank Liquidity Holdings (liqhod)*
Post TARP × TARP Recipient	**-0.262*** **			
	(0.00)			
TARP Recipient	0.117***			
	(0.00)			
Post TARP	0.049***			
	(0.00)			
TARP amount				**-0.001*** **
				(0.00)
ca	0.059***	-3.318***	2.963***	0.030***
	(0.02)	(0.20)	(0.18)	(0.00)
aq	0.224***	8.543***	31.697***	-0.357***
	(0.08)	(1.27)	(1.05)	(0.03)
roe	-0.074***	-0.910***	1.933***	-0.070***
	(0.01)	(0.08)	(0.08)	(0.00)
bhc	-0.011***	0.996***	1.155***	-0.010***
	(0.00)	(0.02)	(0.02)	(0.00)
fedfunds	-0.009***	0.033***	0.012	-0.009***
	(0.00)	(0.01)	(0.01)	(0.00)
spread	-0.007***	-0.003	0.023*	-0.005***
	(0.00)	(0.02)	(0.01)	(0.00)
lngdp	0.054***	-0.851***	-0.565***	0.039***
	(0.00)	(0.16)	(0.14)	(0.00)
lngpsave	-0.027***	0.020	-0.236**	0.038***
	(0.00)	(0.13)	(0.11)	(0.00)
lnperinc	-0.006*	0.697***	-0.104***	0.001
	(0.00)	(0.04)	(0.03)	(0.00)
lnemploy	0.003	0.094***	0.604***	0.000
	(0.00)	(0.03)	(0.03)	(0.00)

lnpop	-0.003	0.488***	-0.200***	0.000
	(0.00)	(0.03)	(0.03)	(0.00)
crisisdummy	-0.017***	0.067***	-0.018	-0.018***
	(0.00)	(0.02)	(0.01)	(0.00)
hhi_dep	-0.003***	0.841***	0.717***	-0.004***
	(0.00)	(0.01)	(0.01)	(0.00)
Feddirector		0.840***	0.691***	
		(0.04)	(0.02)	
SubcommonFI		0.447***	-0.036*	
		(0.03)	(0.02)	
LocalFIREdonation		-2.299***	-0.585**	
		(0.30)	(0.24)	
Dem		-0.250***	0.021	
		(0.03)	(0.02)	
Residual				-0.000*
				(0.00)
Constant	-0.162***	-7.966***	19.150***	-0.588***
	(0.02)	(0.91)	(0.78)	(0.02)
Observations	268,995	267,961	267,961	267,961
R-squared	0.168	0.140	0.431	0.150

Note: Column (1) of this table presents the results of DID combined with Erickson-Whited high-order cumulant estimators analysing Eq. (1) and (2) for the impact of TARP on bank liquidity holdings. Column (2) and (3) of this table report estimates from two-part model analysing Eq. (3) and (4) to address the potential selection bias caused by the non-random TARP funding and the endogeneity problem induced by the "precautionary" and "strategic" motive for liquidity holdings. As shown, the first part models the probability of receiving TARP funds using the logit model while the second part models the distribution of the TARP amount to be received if applied for it and if approved by using the OLS regression. The predicted residual value, *Residual*, estimated after the two-part model, is added as an additional regressor in the main estimation Eq. (5) to examine the effect of TARP capital infusion on bank liquidity holdings (Column (4)). Bootstrapping (with 1,000 replications) is used to estimate standard error. *TARP Recipient* takes the value of one if a bank is TARP recipient and zero otherwise. *Post TARP* is a dummy equal to one in 2009-2014, the period after TARP program initiation and zero otherwise. The variable descriptions are in Appendix 3.1. Robust standard errors in brackets below each coefficient estimate. *, **, and *** denote significance at 10%, 5% and 1% level, respectively.

3.6 Additional test

3.6.1 The impact of TARP on bank liquidity creation

To test the sub-hypothesis that higher government capital support is associated with higher levels of bank liquidity creation, I use the BB measure (*catfat_gta*) as a proxy for total liquidity creation. Berger and Bouwman (2009) provide the first comprehensive measure of bank liquidity creation that takes into account the contribution of all bank assets, liabilities, equity, and off-balance sheet activities.[29] To better understand the driving forces behind the increases in liquidity creation, I decompose liquidity creation into on-balance sheet liquidity creation (*catnonfat_gta*) and off-balance sheet liquidity creation (*lc_obs_gta*). To enhance my analysis, I further decompose on-balance sheet liquidity creation into asset-side liquidity creation (*lc_a_gta*) and liability-side liquidity creation (*lc_l_gta*). Following Berger, Bouwman, Kick and Schaeck (2016), I examine asset-side liquidity creation by looking directly at lending because lending is a key component of asset-side liquidity creation. I focus on total loans (*taln*) as well as two main lending categories: corporate loans (*crln*) and retail loans (*rtln*) (all scaled by total assets). The results are presented in Table 3.4.

As shown in Panel A of Table 3.4, I find that the estimated coefficient of the DID term, *Post TARP*×*TARP Recipient*, is significantly positively related to aggregate bank liquidity creation (*catfat_gta*) across all specifications. This result is consistent with my hypothesis that TARP capital support can encourage banks to create more liquidity. In terms of control variables, I find that higher capital (*ca*) reduces liquidity creation. This finding is aligned with the "financial fragility-crowding out" hypothesis (Diamond and Rajan, 2000, 2001; Gorton and Winton, 2017). I also find that bank holding companies (*bhc*) and banks with higher earnings (*roe*) create more liquidity. As expected, liquidity risk (*ucrt*) and bank risk-taking (*ristak*) are positively related to liquidity creation, suggesting that liquidity creation is risky. As can be seen from Panel B, a similar result is obtained when I examine the relationship between TARP capital

[29] I am grateful to Christa Bouwman for providing the bank liquidity creation data. It is downloadable from Christa Bouwman's personal website (https://sites.google.com/a/tamu.edu/bouwman/data).

infusion and on-balance sheet liquidity creation only (*catnonfat_gta*). Panel C shows that the relationship between TARP capital support and off-balance sheet liquidity creation (*lc_obs_gta*) is negative and significant. However, the magnitude of the coefficient estimates is much smaller than the one found using on-balance sheet liquidity creation (*catnonfat_gta*). In other words, TARP capital support significantly increases on-balance sheet liquidity creation but marginally reduces off-balance sheet liquidity creation, explaining why I find an overall positive effect of TARP capital support on the total liquidity creation of banks. In Panel D and E, I further decompose on-balance liquidity creation (*catnonfat_gta*) into asset-side (*lc_a_gta*) and liability-side (*lc_l_gta*) liquidity creation, and find that the effect of TARP is more pronounced for asset-side liquidity creation. I also directly investigate the impact of TARP capital infusion on bank lending in Panel F-H. In general, I find that TARP has a positive effect on lending, which is consistent with my finding that TARP capital support increases asset-side liquidity creation. This result is also consistent with recent findings of for example, Li (2013), that there is a positive effect of TARP capital infusion on bank lending.

Table 3.4 The effect of TARP on bank liquidity creation: DID estimation results

Panel A: VARIABLES	Model (1) *catfat_gta*	Model (2) *catfat_gta*	Model (3) *catfat_gta*	Model (4) *catfat_gta*
Post TARP × TARP Recipient	**0.012*** **	**0.012*** **	**0.009*** **	**0.009*** **
	(0.00)	(0.00)	(0.00)	(0.00)
TARP Recipient	-0.002**	-0.002*		
	(0.00)	(0.00)		
Post TARP	0.003***		0.001	
	(0.00)		(0.00)	
ca	-0.970***	-0.966***	-0.769***	-0.758***
	(0.01)	(0.01)	(0.02)	(0.02)
aq	0.157***	0.240***	-0.008	0.129
	(0.04)	(0.04)	(0.08)	(0.09)
roe	0.118***	0.118***	0.105***	0.107***
	(0.00)	(0.00)	(0.00)	(0.01)
bhc	0.017***	0.017***	0.003	0.005
	(0.00)	(0.00)	(0.00)	(0.00)
ucrt	0.373***	0.370***	0.254***	0.244***
	(0.00)	(0.00)	(0.01)	(0.01)
ristak	0.942***	0.944***	0.820***	0.826***
	(0.00)	(0.00)	(0.01)	(0.01)
fedfunds	-0.007***	-0.009	-0.006***	0.107***
	(0.00)	(885.79)	(0.00)	(0.04)
spread	-0.001***	-0.001	-0.000	0.040***
	(0.00)	(365.42)	(0.00)	(0.01)
lngdp	0.197***	0.213	0.228***	0.988***
	(0.00)	(6,537.60)	(0.01)	(0.21)
lngpsave	-0.064***	-0.064	-0.062***	-0.439***
	(0.00)	(3,457.29)	(0.00)	(0.10)
lnperinc	0.007***	0.009***	-0.011	0.001
	(0.00)	(0.00)	(0.01)	(0.01)
lnemploy	0.017***	0.017***	0.044***	0.032***
	(0.00)	(0.00)	(0.01)	(0.01)
lnpop	-0.005***	-0.004***	-0.036***	-0.024**
	(0.00)	(0.00)	(0.01)	(0.01)
crisisdummy	-0.027***	-0.022	-0.024***	0.030**
	(0.00)	(392.06)	(0.00)	(0.01)
hhi_dep	0.012***	0.013***	0.009***	0.008***
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-1.871***	-2.035	-1.837***	-6.418***
	(0.03)	(36,213.81)	(0.05)	(1.28)
Year_quarter FE	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes
Observations	268,995	268,995	268,995	268,995
R-squared	0.742	0.743	0.595	0.602

Panel B: VARIABLES	Model (1) *catnonfat_gta*	Model (2) *catnonfat_gta*	Model (3) *catnonfat_gta*	Model (4) *catnonfat_gta*
Post TARP × TARP Recipient	**0.013*** **	**0.013*** **	**0.011*** **	**0.011*** **
	(0.00)	(0.00)	(0.00)	(0.00)
TARP Recipient	-0.005***	-0.005***		
	(0.00)	(0.00)		
Post TARP	0.004***		0.001*	
	(0.00)		(0.00)	
Year_quarter FE	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes
Observations	268,995	268,995	268,995	268,995
R-squared	0.680	0.682	0.571	0.580

Panel C: VARIABLES	Model (1) *lc_obs_gta*	Model (2) *lc_obs_gta*	Model (3) *lc_obs_gta*	Model (4) *lc_obs_gta*
Post TARP × TARP Recipient	**-0.002*** **	**-0.002*** **	**-0.001** **	**-0.001** **
	(0.00)	(0.00)	(0.00)	(0.00)
TARP Recipient	0.004***	0.004***		
	(0.00)	(0.00)		
Post TARP	-0.001***		-0.001***	
	(0.00)		(0.00)	
Year_quarter FE	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes
Observations	268,995	268,995	268,995	268,995
R-squared	0.879	0.879	0.801	0.801

Panel D: VARIABLES	Model (1) *lc_a_gta*	Model (2) *lc_a_gta*	Model (3) *lc_a_gta*	Model (4) *lc_a_gta*
Post TARP × TARP Recipient	**0.009*** **	**0.009*** **	**0.009*** **	**0.009*** **
	(0.00)	(0.00)	(0.00)	(0.00)
TARP Recipient	0.006***	0.006***		
	(0.00)	(0.00)		
Post TARP	-0.002*		-0.006***	
	(0.00)		(0.00)	
Year_quarter FE	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes
Observations	268,995	268,995	268,995	268,995
R-squared	0.781	0.781	0.680	0.682

Panel E: VARIABLES	Model (1) *lc_l_gta*	Model (2) *lc_l_gta*	Model (3) *lc_l_gta*	Model (4) *lc_l_gta*
Post TARP × TARP Recipient	**0.004*** **	**0.004*** **	**0.002**	**0.002**
	(0.00)	(0.00)	(0.00)	(0.00)
TARP Recipient	-0.012***	-0.012***		
	(0.00)	(0.00)		
Post TARP	0.006***		0.007***	
	(0.00)		(0.00)	
Year_quarter FE	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes
Observations	268,995	268,995	268,995	268,995
R-squared	0.344	0.355	0.445	0.492

Panel F: VARIABLES	Model (1) *taln*	Model (2) *taln*	Model (3) *taln*	Model (4) *taln*
Post TARP × TARP Recipient	**0.008*** **	**0.008*** **	**0.013*** **	**0.012*** **
	(0.00)	(0.00)	(0.00)	(0.00)
TARP Recipient	0.003***	0.004***		
	(0.00)	(0.00)		
Post TARP	-0.006***		-0.007***	
	(0.00)		(0.00)	
Year_quarter FE	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes
Observations	268,995	268,995	268,995	268,995
R-squared	0.732	0.733	0.658	0.660

Panel G: VARIABLES	Model (1) *crln*	Model (2) *crln*	Model (3) *crln*	Model (4) *crln*
Post TARP × TARP Recipient	**0.003*****	**0.003*****	**0.001**	**0.000**
	(0.00)	(0.00)	(0.00)	(0.00)
TARP Recipient	0.007***	0.007***		
	(0.00)	(0.00)		
Post TARP	-0.003***		-0.003***	
	(0.00)		(0.00)	
Year_quarter FE	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes
Observations	268,995	268,995	268,995	268,995
R-squared	0.221	0.221	0.173	0.174

Panel H: VARIABLES	Model (1) *rtln*	Model (2) *rtln*	Model (3) *rtln*	Model (4) *rtln*
Post TARP × TARP Recipient	**0.002*****	**0.002*****	**0.004*****	**0.004*****
	(0.00)	(0.00)	(0.00)	(0.00)
TARP Recipient	-0.004***	-0.004***		
	(0.00)	(0.00)		
Post TARP	-0.005***		-0.003***	
	(0.00)		(0.00)	
Year_quarter FE	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes
Observations	268,995	268,995	268,995	268,995
R-squared	0.189	0.193	0.305	0.309

Note: This table reports estimates from difference-in-difference (DID) regression analysing Eq. (1) for the impact of TARP on bank liquidity creation. The dependent variable is *Bank Liquidity Creation.* Five different proxies for bank liquidity creation are used. Panel A shows the results for total liquidity creation, proxied by *catfat_gta.* I also decompose total liquidity creation into on-balance sheet liquidity creation (*catnonfat_gta* in Panel B) and off-balance sheet liquidity creation (*lc_obs_gta* in Panel C). Further, I decompose on-balance sheet liquidity creation into asset-side liquidity creation (*lc_a_gta* in Panel D) and liability-side liquidity creation (*lc_l_gta* in Panel E). I also directly examine the impact of TARP on lending by looking at total loans (*taln*), corporate loans (*crln*) and retail loans (*rtln*) in Panel F-H, respectively (all scaled by total assets). All control variables in the baseline model are included across all specifications in Panel B-H (not shown for brevity). *TARP Recipient* takes the value of one if a bank is TARP recipient and zero otherwise. *Post TARP* is a dummy equal to one in 2009-2014, the period after TARP program initiation and zero otherwise. The variable descriptions are in Appendix 3.1. Model (2)-(4) report the results of OLS regressions, which include different Fixed Effects (FE) estimations (Year_quarter FE and Bank FE). *TARP Recipient* term is absorbed in individual fixed effects. *Post TARP* term is subsumed in time fixed effects. Robust standard error is shown in bracket below each coefficient estimate. *, **, and *** denote significance at 10%, 5% and 1% level, respectively.

3.6.2 Does the relationship between TARP and bank liquidity holdings vary with different bank capitalization levels?

It is widely recognised that the main objective of TARP was to restore the liquidity and stability to the financial system through capital injection. My key finding is that TARP capital support can unlock liquidity holdings by banks. To address whether healthy or unhealthy banks react more intensively to capital support, I split the sample at the median equity ratio[30] and test whether the effect of TARP differs between high- and low-capitalized banks. High-capitalized (low-capitalized) subsamples include banks with the equity capital ratio above (equal or below) the median. I find that my main conclusions hold in both subsamples. Table 3.5 presents these results.

As noted in Table 3.5, the coefficient on the DID term *Post TARP×TARP Recipient* is negative and statistically significant in all specifications for both high-capitalized and low-capitalized banks, confirming my conjecture that TARP capital support can mitigate high levels of inefficient liquidity holdings of banks. The magnitude of the coefficient estimate is comparable to that reported in Table 3.2 for the full sample, suggesting that the results are robust to bank capital levels. In other words, I find no evidence that poorly-capitalized banks behave different from well-capitalized banks when receiving TARP.

[30] Banks' Tier 1 capital ratio improved considerably with the TARP injections because the preferred stock purchased by the Treasury Department were treated as Tier 1 capital for regulatory purposes. To eliminate the impact of TARP on the choice of bank capitalization, I divide the full sample into well-capitalized and poorly-capitalized banks based on the median level of equity capital to total asset ratio because the equity capital ratio was less affected by TARP.

Table 3.5 Does the relationship between TARP and bank liquidity holdings vary with bank capitalization?

Panel A: Poorly-capitalized banks

VARIABLES	Model (1) *liqhod*	Model (2) *liqhod*	Model (3) *liqhod*	Model (4) *liqhod*
Post TARP × TARP Recipient	**-0.009*****	**-0.009*****	**-0.008*****	**-0.008*****
	(0.00)	(0.00)	(0.00)	(0.00)
TARP Recipient	-0.008***	-0.008***		
	(0.00)	(0.00)		
Post TARP	0.021***		0.020***	
	(0.00)		(0.00)	
Baseline Controls	Yes	Yes	Yes	Yes
Year_quarter FE	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes
Observations	134,529	134,529	134,529	134,529
R-squared	0.183	0.192	0.230	0.244

Panel B: Well-capitalized banks

VARIABLES	Model (1) *liqhod*	Model (2) *liqhod*	Model (3) *liqhod*	Model (4) *liqhod*
Post TARP × TARP Recipient	**-0.008*****	**-0.008*****	**-0.011*****	**-0.010*****
	(0.00)	(0.00)	(0.00)	(0.00)
TARP Recipient	-0.011***	-0.011***		
	(0.00)	(0.00)		
Post TARP	0.022***		0.022***	
	(0.00)		(0.00)	
Baseline Controls	Yes	Yes	Yes	Yes
Year_quarter FE	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes
Observations	134,466	134,466	134,466	134,466
R-squared	0.133	0.137	0.214	0.224

Note: This table reports estimates from difference-in-difference (DID) regression analysing Eq. (1) for the impact of TARP on liquidity holdings by banks. *TARP Recipient* takes the value of one if a bank is TARP recipient and zero otherwise. *Post TARP* is a dummy equal to one in 2009-2014, the period after TARP program initiation and zero otherwise. I separate the sample into two subsamples: well-capitalized banks (with the equity capital ratio above the median level of the distribution) and poorly-capitalized banks (with the equity capital ratio below or equal to the median level of the distribution). Model (2)-(4) report the results of OLS regressions, which include different Fixed Effects (FE) estimations (Year_quarter FE and Bank FE). *TARP Recipient* term is absorbed in individual fixed effects. *Post TARP* term is subsumed in time fixed effects. All control variables in the baseline model are included across all specifications in this table, not shown for brevity's sake. The variable descriptions are in Appendix 3.1. Robust standard error in bracket is shown below each coefficient estimate. *, **, and *** denote significance at 10%, 5% and 1% level, respectively.

3.6.3 Splitting the sample of banks into different size categories

One may argue that the hypothesized effect of TARP capital support on bank liquidity holdings may differ between bank sizes. In corporate finance, small firms face more borrowing constraints and pay more for external financing than large firms (Whited, 1992; Fazzari and Petersen, 1993; Kim, Mauer and Sherman, 1998). Opler, Pinkowitz, Stulz and Williamson (1999) found that small firms have restricted access to external capital markets. Along the same line, Allen, Peristiani and Saunders (1989) argue that small banks face greater information asymmetry which makes it costly for them to access the interbank market. Hence, small banks may accumulate/strengthen their capital and liquidity positions upon receiving government support in order to avoid external financing constraints and possible costly default. In contrast, large banks are typically associated with less severe information asymmetry problems and have more easy access to funding from national or international capital markets. Thus, large banks are less likely to hoard liquidity upon receiving government support. To confirm that my results are robust, I do additional tests by splitting my sample in four different ways by bank size, and perform the analyses separately for small and large banks.

According to industry definitions, I firstly define small banks as those with total assets less than \$1 billion, medium banks as those with total assets between \$1 billion and \$3 billion, and large banks as those with total assets more than \$3 billion. Secondly, I use an alternative cutoff of \$5 billion to separate medium and large banks whilst I retain \$1 billion cutoff for small banks. Thirdly, I split my sample of banks using a cutoff of \$1 billion dollars in assets, because banks with sizes below \$1 billion are generally considered to be community banks and \$1 billion is also used as the traditional dividing line to distinguish between small and large banks throughout much of the empirical banking literature (Berger and Sedunov, 2017). Finally, very large banks may be considered too-big-to-fail (TBTF), and in the event of distress, they tend to receive government support. To make sure that my large-bank results are not overly influenced by TBTF banks, I rerun the \$1 billion cutoff analysis while excluding these banks. Following the 2010 Dodd-Frank Act, I define TBTF banks as those with total assets exceeding \$50 billion. The results are shown in Table 3.6. As shown in Table 3.6, all the original DID model findings are essentially unchanged. The highly significant and negative coefficients of the DID term *Post TARP×TARP Recipient* across different bank size categories confirm the original findings that there is a negative and significant relationship between TARP and bank liquidity holdings. The magnitude of the coefficient is also similar to that reported in the main results in Table 3.2.

Table 3.6 The effect of TARP on bank liquidity holdings: splitting the sample of banks into different size categories

Panel A: $1 billion and $3 billion size cutoff

Small banks VARIABLES	Model (1) *liqhod*	Model (2) *liqhod*	Model (3) *liqhod*	Model (4) *liqhod*
Post TARP × TARP Recipient	**-0.007*****	**-0.007*****	**-0.008*****	**-0.008*****
	(0.00)	(0.00)	(0.00)	(0.00)
TARP Recipient	-0.009***	-0.009***		
	(0.00)	(0.00)		
Post TARP	0.021***		0.020***	
	(0.00)		(0.00)	
Baseline Controls	Yes	Yes	Yes	Yes
Year_quarter FE	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes
Observations	251,309	251,309	251,309	251,309
R-squared	0.155	0.161	0.235	0.246

Medium banks VARIABLES	Model (1) *liqhod*	Model (2) *liqhod*	Model (3) *liqhod*	Model (4) *liqhod*
Post TARP × TARP Recipient	**-0.011*****	**-0.011*****	**-0.014****	**-0.015****
	(0.00)	(0.00)	(0.01)	(0.01)
TARP Recipient	-0.003***	-0.003***		
	(0.00)	(0.00)		
Post TARP	0.027***		0.027***	
	(0.00)		(0.00)	
Baseline Controls	Yes	Yes	Yes	Yes
Year_quarter FE	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes
Observations	11,416	11,416	11,416	11,416
R-squared	0.194	0.202	0.213	0.233

Large banks VARIABLES	Model (1) *liqhod*	Model (2) *liqhod*	Model (3) *liqhod*	Model (4) *liqhod*
Post TARP × TARP Recipient	**-0.005***	**-0.005***	**-0.016****	**-0.015****
	(0.00)	(0.00)	(0.01)	(0.01)
TARP Recipient	-0.008***	-0.008***		
	(0.00)	(0.00)		
Post TARP	0.019***		0.020***	
	(0.01)		(0.01)	
Baseline Controls	Yes	Yes	Yes	Yes
Year_quarter FE	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes
Observations	6,270	6,270	6,270	6,270
R-squared	0.147	0.153	0.175	0.188

Panel B: $1 billion and $5 billion size cutoff

	Model (1) *Small banks*	Model (2) *Medium banks*	Model (3) *Large banks*
VARIABLES	*liqhod*	*liqhod*	*liqhod*
Post TARP × TARP Recipient	**-0.008*****	**-0.012****	**-0.016***
	(0.00)	(0.01)	(0.01)
Baseline Controls	Yes	Yes	Yes
Year_quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Observations	251,309	13,403	4,283
R-squared	0.246	0.238	0.167

Panel C: $1 billion size cutoff

	(1) *Small banks*	(2) *Large banks with TBTF banks**	(3) *Large banks without TBTF banks*
VARIABLES	*liqhod*	*liqhod*	*liqhod*
Post TARP × TARP Recipient	**-0.008*****	**-0.016*****	**-0.016*****
	(0.00)	(0.00)	(0.00)
Baseline Controls	Yes	Yes	Yes
Year_quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Observations	251,309	17,686	16,661
R-squared	0.246	0.211	0.217

*TBTF banks = "Too big to fail" banks

Note: This table reports estimates from difference-in-difference (DID) regression analysing Eq. (1) for the impact of TARP on bank liquidity holdings by bank size. I sort the sample banks into large, medium and small banks based on different size cutoffs in Panel A, B and C. *TARP Recipient* takes the value of one if a bank is TARP recipient and zero otherwise. *Post TARP* is a dummy equal to one in 2009-2014, the period after TARP program initiation and zero otherwise. All control variables in the baseline model are included across all specifications in this table, not shown for brevity. Panel A reports the results of OLS regressions, which include different Fixed Effects (FE) estimations (Year_quarter FE and Bank FE). *TARP Recipient* term is absorbed in individual fixed effects. *Post TARP* term is subsumed in time fixed effects. In the interest of brevity, I only report the specifications that include all fixed effects in Panel B and C. The variable descriptions are in Appendix 3.1. Robust standard error in bracket is shown below each coefficient estimate. *, **, and *** denote significance at 10%, 5% and 1% level, respectively.

3.6.4 Using an alternative bank liquidity ratio

For robustness, following Cornett, McNutt, Strahan and Tehranian (2011) and Berrospide (2013), I use an alternative measure of bank liquidity ratio, defined as the sum of all cash and balances due from other financial institutions, fed funds sold less fed funds bought, and securities purchased under resale agreements less securities sold under repurchase agreements, and available-for-sale securities, scaled by total assets. Table 3.7 reports the results.

Table 3.7 shows that the coefficient of the DID term *Post TARP×TARP Recipient* is highly negative and significant across all specifications in terms of the relationship between TARP and bank liquidity holdings. These results provide evidence to support the view that government capital support alleviates liquidity holdings burdens of banks. The magnitude of the coefficient estimate is also comparable to that reported in Table 3.2. All control variables show similar signs and similar significance as previous results. All in all, the results are robust in terms of this alternative measure of bank liquidity ratio.

Table 3.7 The effect of TARP on bank liquidity holdings: an alternative bank liquidity ratio

VARIABLES	Model (1) *liqhodr*	Model (2) *liqhodr*	Model (3) *liqhodr*	Model (4) *liqhodr*
Post TARP × TARP Recipient	**-0.005*** **	**-0.004*** **	**-0.012*** **	**-0.012*** **
	(0.00)	(0.00)	(0.00)	(0.00)
TARP Recipient	-0.033***	-0.033***		
	(0.00)	(0.00)		
Post TARP	0.025***		0.023***	
	(0.00)		(0.00)	
ca	0.527***	0.524***	0.280***	0.280***
	(0.01)	(0.01)	(0.03)	(0.03)
aq	-3.984***	-4.190***	-1.455***	-1.574***
	(0.05)	(0.06)	(0.08)	(0.09)
roe	-0.131***	-0.155***	-0.142***	-0.168***
	(0.00)	(0.00)	(0.01)	(0.01)
bhc	-0.017***	-0.017***	-0.025***	-0.024***
	(0.00)	(0.00)	(0.00)	(0.00)
fedfunds	-0.017***	-0.000	-0.016***	0.115**
	(0.00)	(.)	(0.00)	(0.06)
spread	-0.013***	0.040	-0.013***	0.084***
	(0.00)	(.)	(0.00)	(0.02)
lngdp	0.052***	0.714	0.039***	1.447***
	(0.01)	(.)	(0.01)	(0.34)
lngpsave	-0.097***	-0.581	-0.117***	-0.972***
	(0.01)	(.)	(0.00)	(0.16)
lnperinc	0.004**	0.004**	0.057***	0.062***
	(0.00)	(0.00)	(0.01)	(0.01)
lnemploy	-0.026***	-0.026***	-0.030**	-0.033**
	(0.00)	(0.00)	(0.01)	(0.01)
lnpop	0.009***	0.009***	0.003	0.007
	(0.00)	(0.00)	(0.02)	(0.02)
crisisdummy	-0.033***	0.007	-0.034***	0.042*
	(0.00)	(.)	(0.00)	(0.02)
hhi_dep	-0.011***	-0.011***	-0.002	-0.003
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.712***	-1.908	0.589***	-6.457***
	(0.05)	(.)	(0.07)	(2.10)
Year_quarter FE	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes
Observations	268,995	268,995	268,995	268,995
R-squared	0.109	0.114	0.119	0.137

Note: This table reports estimates from difference-in-difference (DID) regression analysing Eq. (1) for the impact of TARP on bank liquidity holdings. I use an alternative measure of bank liquidity ratio (*liqhodr*), defined as the sum of all cash and balances due from other financial institutions, fed funds sold less fed funds bought, and securities purchased under resale agreements less securities sold under repurchase agreements, and available-for-sale securities, scaled by total assets. *TARP Recipient* takes the value of one if a bank is TARP recipient and zero otherwise. *Post TARP* is a dummy equal to one in 2009-2014, the period after TARP program initiation and zero otherwise. Model (2)-(4) report the results of OLS regressions, which include different Fixed Effects (FE) estimations (Year_quarter FE and Bank FE). *TARP Recipient* term is absorbed in individual fixed effects. *Post TARP* term is subsumed in time fixed effects. The variable descriptions are in Appendix 3.1. Robust standard error in bracket is shown below each coefficient estimate. *, **, and *** denote significance at 10%, 5% and 1% level, respectively.

3.6.5 Using alternative measures of bank control variables

The applicability of the CAMELS proxies used in the original analysis in this paper are tested to check the robustness of my findings with a different set of bank fundamental indicators. Capital adequacy (*car*) is measured as the tier-1 risk-based capital ratio; asset quality (*aqr*) is measured by the ratio of all nonperforming assets (the sum of assets past due 30 to 89 days, assets past due 90 days or more and assets in nonaccrual status) to total assets; earnings (*roa*) is computed by the ratio of net income to total assets. The findings, based on these alternative measures, are reported in Table 3.8. As shown, the results are robust to using alternative measures of bank control variables and support the previous findings that TARP has a significant and negative effect on bank liquidity holdings in terms of the coefficient of the DID term, *Post TARP×TARP Recipient*. The bank control variable coefficients are also similar to those presented in Table 3.2.

Table 3.8 The effect of TARP on bank liquidity holdings: alternative measures of bank controls

VARIABLES	Model (1) *liqhod*	Model (2) *liqhod*	Model (3) *liqhod*	Model (4) *liqhod*
Post TARP × TARP Recipient	**-0.011*****	**-0.011*****	**-0.012*****	**-0.012*****
	(0.00)	(0.00)	(0.00)	(0.00)
TARP Recipient	-0.005***	-0.005***		
	(0.00)	(0.00)		
Post TARP	0.042***		0.041***	
	(0.00)		(0.00)	
car	0.133***	0.126***	0.096***	0.071***
	(0.00)	(0.00)	(0.01)	(0.01)
aqr	-0.058***	-0.037***	-0.035**	-0.003
	(0.01)	(0.01)	(0.02)	(0.02)
roa	-0.644***	-0.847***	-0.449***	-0.718***
	(0.02)	(0.02)	(0.04)	(0.04)
bhc	-0.005***	-0.005***	-0.002	-0.002
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.034***	0.042***	0.035***	0.047***
	(0.00)	(0.00)	(0.00)	(0.00)
Year_quarter FE	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes
Observations	269,094	269,094	269,094	269,094
R-squared	0.152	0.175	0.201	0.243

Note: This table reports estimates from difference-in-difference (DID) regression analysing Eq. (1) for the impact of TARP on bank liquidity holdings. To mitigate the concern that my results may be sensitive to CAMELS proxies, I use alternative measures of bank conditions. *TARP Recipient* takes the value of one if a bank is TARP recipient and zero otherwise. *Post TARP* is a dummy equal to one in 2009-2014, the period after TARP program initiation and zero otherwise. Model (2)-(4) report the results of OLS regressions, which include different Fixed Effects (FE) estimations (Year_quarter FE and Bank FE). *TARP Recipient* term is absorbed in individual fixed effects. *Post TARP* term is subsumed in time fixed effects. For brevity's sake, I only present specifications that include all bank control variables. The variable descriptions are in Appendix 3.1. Robust standard error in bracket is shown below each coefficient estimate. *, **, and *** denote significance at 10%, 5% and 1% level, respectively.

3.7 Conclusion

In this paper, I test whether and how TARP capital support influences the liquidity hoarding of banks. There are undesirable outcomes associated with banks' liquidity hoarding behaviour. First and foremost, as the recent financial crisis demonstrates, liquidity hoarding affects the normal functioning of the interbank market. Liquidity hoarding may prevent the efficient reallocation of liquidity that occur from liquidity surplus banks to deficit banks (Acharya, Gromb and Yorulmazer, 2012), which in turn results in the drying up of liquidity in the interbank market. Liquidity hoarding may also create inefficiency in the sense that illiquid banks can be priced out of the market for cash and forced into bankruptcy at the same time as liquid banks are hoarding cash instead of supplying it to the market (Gale and Yorulmazer, 2013). Secondly, inefficiency may arise from the fact that excessive liquidity hoarding is costly for banks because the return on these assets is low compared to the alternative use of these funds. In addition, a large balance of highly liquid assets gives managers a great deal of discretion, and is likely to increase agency costs and exacerbate managerial agency problems (Myers and Rajan, 1998). Thirdly, liquidity hoarding may lead to systemic risk through spill-over effects since the start of liquidity hoarding and asset fire sale actions by stressed banks can trigger down other banks (Diamond and Rajan, 2011). Last but not least, liquidity hoarding by banks may constrain the effectiveness of policy intervention. The evaporation of the interbank market liquidity sources that emanated in the summer of 2007 resulted in dependence on central bank liquidity support for most banks. It was part of the policymaker's first line of defense and exceeded historical levels by far (Laeven and Valencia, 2012). However, the incentives of banks to stock liquid assets during the recent financial crisis could have dampened the effect of massive liquidity injections[31] by central banks to restore the interbank market and revive the economy (Heider, Hoerova and Holthausen, 2015).

Based on the evidence that banks' precautionary and strategic demand for liquidity may be excessive and inefficient (e.g., during the recent financial crisis 2007-

[31] Aside from its use of conventional policy and liquidity facilities, such as open market operations and discount window, the Federal Reserve supplied abundant liquidity to the banking system via a broader range of new and expanded liquidity facilities, for example, the Term Auction Facility (TAF) and bilateral currency swap agreements with several foreign central banks. Fleming (2012) discussed the unprecedented level of liquidity provision by the Federal Reserve during the recent financial crisis.

2009), it would suggest possible policy interventions to address excessive hoarding of liquidity by banks in future. The results presented in this study show that higher government capital support (TARP) is associated with lower levels of bank liquidity holdings, consistent with the precautionary and strategic motives of liquidity holdings in the banking literature. I did a number of robustness checks and found further supportive evidence for my interpretation. First, this finding is robust to a number of different empirical specifications, including difference-in-difference techniques, Erickson-Whited high-order cumulant estimators and two-part models. Secondly, the results are also robust to splitting the sample by bank capitalization and bank size. There is no evidence that poorly-capitalized banks and/or small banks behave significantly different from well-capitalized banks and/or large banks upon receiving TARP capital support. Third, my findings continue to hold when I use alternative measures of bank liquidity ratios and bank control variables. Finally, further analysis reveals that the TARP program not only unlocked liquidity holdings but also achieved the stated purpose of increasing bank lending/liquidity creation. However, it is still an open question as to how other factors, such as bank organization structure and bank governance, may affect government bailout of banks. These interesting issues are beyond the scope of this paper, but may be pursued in future research.

Appendix 3.1 Variable definitions

Variable	Definition
Panel A: Bank liquidity and TARP variables	
liqhod	The sum of all cash and balances due from other financial institutions, scaled by total assets
liqhodr	The sum of all cash and balances due from other financial institutions, fed funds sold less fed funds bought, and securities purchased under resale agreements less securities sold under repurchase agreements, and available-for-sale securities, scaled by total assets
catfat_gta	Dollar amount of "*catfat*" liquidity creation normalized by gross total assets. The "*catfat*" measures the liquidity created on and off the balance sheet, following Berger and Bouwman (2009)
catnonfat_gta	Dollar amount of "*catnonfat*" liquidity creation normalized by gross total asset. The "*catnonfat*" measures the liquidity created on the balance sheet, following Berger and Bouwman (2009)
lc_obs_gta	Dollar amount of "*lc_obs_gta*" liquidity creation normalized by gross total asset. The "*lc_obs_gta*" measures the liquidity created off the balance sheet, following Berger and Bouwman (2009)
taln	Total loans and leases scaled by total assets
crln	Commercial and industrial loans scaled by total assets
rtln	Loans to individuals scaled by total assets
TARP amount	The natural log of the amount of the TARP funds
TARP dummy	Takes the value of one if a bank was TARP recipient and zero otherwise
Panel B: Bank-specific variables	
ca	The ratio of equity capital to total assets
car	The ratio of tier 1 capital to total risk-weighted assets
aq	The ratio of all nonperforming loans (all loans 90 days past due plus all loans charged off) to total assets
aqr	The ratio of all nonperforming assets (the sum of assets past due 30-89 days, assets past due 90 or more days and assets in nonaccrual status) to total assets
roe	The ratio of net income to total equity
roa	The ratio of net income to total assets
bhc	A dummy variable that takes one if bank holding company (BHC) status applies and zero if otherwise
ucrt	The ratio of unused loan commitments to total loans
ristak	The bank's Basel I risk-weighted assets divided by total asset
Panel C: Political and regulatory connection variables	
LocalFIREdonation	The campaign contribution from local finance, insurance, and real estate (FIRE) industries as a percentage of total contribution received by a local political representative in the 2007-2008 election cycle
SubcommonFI	Takes the value of one if a representative sat on the Subcommittee on Financial Institutions and Consumer Credit, which supervises all federal banking regulators, and zero otherwise
Dem	Takes the value of one if a representative was a member of the Democratic Party and zero otherwise
Feddirector	Takes the value of one if an executive of the bank served as a director of a branch of the Fed and zero otherwise

Panel D: Macroeconomic and local economic variables	
fedfunds	The federal funds rate
spread	The spread between 3-month US T-Bills and 10-year US Treasuries
lngdp	Natural logarithm of Gross Domestic Product
lngpsave	Natural logarithm of Gross Private Savings of all US households
lnperinc	Natural logarithm of per capita personal income in a county
lnemploy	Natural logarithm of total employment in a county
lnpop	Natural logarithm of total population in a county
crisisdummy	A dummy variable that equals one from the third quarter of 2007 to the fourth quarter of 2009 and zero otherwise
hhi_dep	Bank-level HHI of deposit concentration for the local markets in which the bank is operating. The local market is defined as the county in which bank headquarter is located

CHAPTER 4

SOCIAL CAPITAL AND BANK LIQUIDITY HOLDINGS

4.1 Introduction

Social capital is best described as the norms and networks that foster cooperation for mutual benefit (Woolcock, 2001). It gained prominence with the widely cited work of Putnam (1993) and Coleman (1988, 1990). Social capital is an environmental paradigm which captures a region's level of reciprocity, trustworthiness, altruism, solidarity, compassion, and propensity to honor obligations. The majority of social capital literature focuses on sociology, political science, accounting, economics and corporate finance (e.g., Ferris, Javakhadze and Rajkovic, 2017; Javakhadze, Ferris and French, 2016a, 2016b; Jha and Cox, 2015; Guiso, Sapienza and Zingales, 2004; La Porta, Shleifer and Vishny, 1997; Buonanno, Montolio and Vanin, 2009; Jha and Chen, 2015; Knack and Keefer, 1997; Rupasingha, Goetz and Freshwater, 2000), but it has received only limited attention in the existing banking research. A growing body of literature has so far focused on the determinants of bank liquidity holdings. For example, Acharya, Shin and Yorulmazer (2011) and Radde (2015) argue that the macroeconomic condition is an important determinant of bank liquidity hoarding, since liquidity hoarding is countercyclical – lower during economic upturns and higher when recessions approach. However, missing from the literature is the idea that non-financial and/or non-macroeconomic factors such as cultural characteristics like social capital might also influence the bank's liquidity holdings. This study makes a contribution to the literature by proposing social capital as a new determinant of bank liquidity holdings.

In this paper, I argue that a bank's social environment may affect the liquidity holdings of a bank headquartered in the community. First, a negative relation between social capital and bank liquidity holdings is expected because social capital may mitigate inefficiently high levels of liquidity holdings by banks through its effects on trust and information-sharing mechanisms. Social capital promotes trust and cooperation among agents, which in turn increases socially efficient collective actions (La Porta, Shleifer and Vishny, 1997). Hence, in high social capital areas, bank depositors/creditors are more likely to trust their banks, reducing liquidity risk (e.g., the probability of bank runs). Social capital also facilitates the sharing of information and reduces information asymmetry within a network by decreasing the intensity of moral hazard and adverse selection and thereby may ease a bank's access to external financing (Javakhadze, Ferris and French, 2016a). Therefore, banks that are located in high social capital areas would face lower levels of liquidity risk and external financing constraints, and they may have weak precautionary motives for hoarding liquidity. Second, social capital may constrain opportunism and corporate misconduct through strong cooperative norms and dense social networks that favour coordination and cooperation. Social peers in high social capital communities are more likely to perceive excessive risk taking and risk shifting behaviour as norm-deviant since these practices are incongruent with the prescribed values and standards associated with civic norms (Hasan, Hoi, Wu and Zhang, 2017a). The dense networks in high social capital regions also facilitate information sharing. It makes monitoring more effective and imposes punishment on divergent behaviour through the disciplinary mechanism of reputation loss by increasing the expected cost to managers for expropriation (Dong, Han, Ke and Chan, 2016). Put differently, the social coercion exercised by members of the same social network can mitigate the unethical behaviour of bank managers. In addition, social capital reduces borrowing firms' inclination for opportunistic actions. Borrowers in high social capital counties are less risky and more trustworthy. Therefore, banks that are located in high social capital areas have less exposure to excessive risk from both bank managers and borrowers, and they have weak precautionary motive to accumulate liquidity buffers against bank risk.

The data from the Northeast Regional Center for Rural Development (NRCRD) at the Pennsylvania State University is used to construct a county-level social capital measure which identifies civic norms and social networks for this research. I match the social capital data with the bank data and conduct a bank-level analysis over the period 2003: Q1 to 2014: Q4 to examine the impact of social capital on the bank liquidity holdings by using a multivariate framework where I control for bank and county characteristics. In line with my expectation, I find that social capital is negatively associated with bank liquidity holdings. The economic impact of social capital is quite significant: holding all other variables constant, a one standard deviation increase in social capital is associated with a 0.16 standard deviation decrease in bank liquidity holdings. These findings serve as profound evidence that social capital plays an important role as a contributing reason for different levels of bank liquidity holdings. The results are robust to alternative model specifications, the use of different variable measurements, and tests for endogeneity.

The contribution of the paper is threefold. First, this study contributes to a more comprehensive understanding of the determinants of bank liquidity holdings. As mentioned earlier, prior research did not consider non-financial factors (e.g., social capital). This study provides an innovative analysis of a previously unexplored factor – the effect of social capital on the bank liquidity holdings. Second, the findings of this paper have important implications for banking regulation under Basel III initiatives. It is well-known that liquidity risk led to the hoarding of liquid assets and widespread bank failures during the global financial crisis (Radde, 2015; DeYoung and Jang, 2016). In response to this, the Basel Committee on Banking Supervision has proposed the Basel III Accord in 2010. It requires banks to adjust their balance sheets to comply with two new liquidity regulations, namely the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR). The evidence in this study indicates that bank supervisors and regulators should not only actively monitor the balance sheets of banks, but also pay special attention to the social capital in the counties where banks are headquartered since social capital affects bank liquidity holdings. This supports the introduction of other criteria to complement the traditional, micro-prudential banking regulation approach. Third, this study contributes to the emerging literature about the effects of social capital on corporate decision-making and behaviour (Javakhadze, Ferris and French, 2016a; Hasan, Hoi, Wu and Zhang, 2017a). In this regard, the results of this research indicate that social capital reduces costly liquidity holdings by banks because social capital may provide banks with assurance of safety. Moreover, the findings also serve as indication that the social environment, in the context of norms and networks surrounding bank headquarters, limit the opportunistic behaviour (e.g., excessive risk taking) of bank management, which in turn alleviates bank risk and precautionary liquidity holdings.

The research is also related to recent literature on professional/managerial and personal connections and networks. Existing literature documents both a “bright” side and “dark” side to these connections. Engelberg, Gao and Parsons (2012) found that personal relationships between employees at firms and their lenders can help borrowers to obtain more favourable financing terms and improve their ex post performance, such as credit ratings and stock returns. Engelberg, Gao and Parsons (2013) found that CEOs with more personal connections to outsiders receive higher salaries and total compensation. Cooney, Madureira, Singh and Yang (2015) found that an investment bank is more likely to be included in the underwriting syndicate when it is connected to the IPO firm through interpersonal social ties between the respective executives and directors. The study of Liu, Luo and Tian (2016) showed that firms of which managers have professional connections, receive more trade credit. Cai and Sevilir (2012) found that social ties between directors of target and acquirer firms improve merger performance. In a similar study, the findings of Huang, Jiang and Yang (2014) showed that directors with investment banking experience help firms earn higher merger announcement returns. Ferris, Javakhadze and Rajkovic (2017) found that managerial social capital is inversely associated with the firm’s cost of equity capital. On the contrary, Cai, Walkling and Yang (2016) found that social connections between the directors and executives of a public firm with investment firms, increase the trading costs of the firms significantly. The study of Ferreira and Matos (2012) provided evidence that a firm benefits from bank involvement in its governance through board representation during a financial crisis, but at the cost of paying higher loan spreads during normal times. Duchin and Sosyura (2013) found that although social connections between divisional managers and CEOs are associated with higher investment efficiency and firm value at firms with high information asymmetry, managerial connections are negatively related to investment efficiency and firm value at firms with weak governance. My paper complements these papers by providing evidence that the local social environment, such as social capital and trust, rather than professional and personal connections, have an important effect on bank management and policy making.

The remainder of this paper is organized as follows. Section 4.2 provides a literature review and the hypotheses emanating from it. Section 4.3 presents the dataset and variable construction. Section 4.4 and 4.5 describes the econometric models and presents the major empirical findings, respectively. Section 4.6 discusses the corrections for possible endogeneity. I consider robustness and some extensions to the basic results in Section 4.7, and then conclude in Section 4.8.

4.2 Literature review and hypotheses development

4.2.1 Literature review

Several studies examine the impact of social capital on financial market development and economic growth. For example, Javakhadze, Ferris and French (2016b) and Guiso, Sapienza and Zingales (2004) found that higher levels of social capital have a positive effect on financial development. Knack and Keefer (1997) found that trust and norms of civic cooperation are associated with stronger economic performance, whereas associational activity is not correlated with economic performance. The level of social capital has a statistically significant, independent positive effect on the rate of per-capita income growth in the U.S. counties (Rupasingha, Goetz and Freshwater, 2000) and is an important determinant of poverty in U.S. counties along with other conventional factors (Rupasingha and Goetz, 2007). In contrast, Peri (2004) found weak evidence that civic involvement fosters economic success.

Literature about social capital also focuses on the impact thereof on businesses. For example, according to Ferris, Javakhadze and Rajkovic (2017), managerial social capital levels inversely affect the equity capital costs of firms. Firms headquartered in U.S. counties with high social capital levels pay lower audit fees (Jha and Chen, 2015) and acquire lower bank loan spreads (Hasan, Hoi, Wu and Zhang, 2017b). Jha and Cox (2015) found that firms in high social capital regions have higher corporate social responsibility (CSR). Javakhadze, Ferris and French (2016a) found that higher social capital levels reduce the dependence of firms on internally generated cash.

However, social capital, as an environmental factor, has received limited attention in existing banking research.[32] Liquidity hoarding phenomena and the massive number of bank failures during the recent financial crisis provide an excellent opportunity for me to investigate whether social capital, defined as the norms and the networks that facilitate collective action (Woolcock, 2001), can mitigate inefficiently high levels of liquidity holdings by banks. In this paper, I link social capital at the county level in the U.S. to a bank headquartered in that county for the following reasons.[33] First, Hasan, Hoi, Wu and Zhang (2017a) found consistent evidence that a community's social capital plays an influential role in the process of decision making of local corporations headquartered in the county. More specifically, they find that social capital at the county level in the U.S. is systematically related to tax avoidance practices of corporations with headquarters located in the counties. Second, it is not unreasonable to expect that liquidity policy and practice formulated at the bank headquarter level would affect liquidity position of all banks under the same roof. According to upper echelons theory (Hambrick, 2007), organizational strategy and performance depend crucially on the managerial characteristics of top management team (TMT) or executive groups, who tend to be clustered in the headquarter. Consistent with this view, Stein (1997) analyses the headquarters' role in an internal capital market and indicates that corporate headquarters have the authority to exercise some control over the allocation of cash flow in the internal capital market. Therefore, county-level social capital may affect a bank's liquidity management via the bank headquarter located in the county.

[32] As far as I know, one strand of the literature shows that social capital, through screening, peer selection and monitoring, enforcement, social sanctions or facilitating informational flow, increases repayment rates in group lending schemes with a reliance on joint liability (see e.g., Karlan, 2007; Cassar, Crowley and Wydick, 2007; Besley and Coate, 1995; Van Tassel, 1999; Ghatak, 1999; Stiglitz, 1990; Banerjee, Besley and Guinnane, 1994; Armendáriz de Aghion, 1999). Additionally, with the rapid development of an emerging Internet-based financial credit market, the new and expanding academic literature in finance examines the role of social capital in online peer-to-peer (P2P) lending outcomes (see e.g., Chen, Zhou and Wan, 2016; Lin, Prabhala and Viswanathan, 2013; Greiner and Wang, 2009).
[33] The measure of social capital in a bank's headquarter county has been used in a number of recent banking, finance and accounting studies (Jin, Kanagaretnam, Lobo and Mathieu, 2017; Hasan, Hoi, Wu and Zhang, 2017a, 2017b; Li, Tang and Jaggi, 2016; Jha and Chen, 2015; Jha and Cox, 2015).

4.2.2 Hypotheses development

Liquidity risk is the main reason for a bank to hold precautionary liquidity (Cornett, McNutt, Strahan and Tehranian, 2011). However, high levels of liquidity holdings may also create inefficiency because the return on liquid assets is low compared with the alternative use of these funds. I argue that social capital may reduce liquidity risk through its effect on trust, contract enforcement and information asymmetry. First, according to Guiso, Sapienza and Zingales (2004), social capital measures the level of mutual trust in a society. Trust and trustworthiness positively correlate across societies (Knack and Keefer, 1997), implying that when banks prove to be trustworthy, creditors will be trusting. The level of social capital in the county where a bank is headquartered can have an impact on how much such bank is trusted by depositors and other bank creditors. Therefore, a bank headquartered in a county with high social capital, will have a lower probability of unexpected mass deposit withdrawals. Hence, lower liquidity risk may result in lower levels of liquidity holdings by banks. Second, social capital facilitates the enforcement of contracts. High social capital regions are more dependent on private enforcement mechanisms for contracts than formal institutions to enforce agreement (Knack and Keefer, 1997). Social capital offers an alternative mechanism of dispute resolution (e.g., social sanction) over contract performance because social rules within social networks stimulate collective actions and impose punishment on divergent and unethical behaviour (e.g., the breach of contract) (Kandori, 1992; McMillan and Woodruff, 2000). Consequently, banks located in high social capital regions may be perceived as more trustworthy/credible and to have a greater propensity to honor an obligation (e.g., meet deposits withdrawals and loan commitments takedowns), which results in lower liquidity risk and thus lower levels of liquidity holdings.

Based on the preceding discussion, I set the following hypotheses for the relationship between social capital and bank liquidity holdings:

H: Banks headquartered in low (high) social capital counties hold high (low) levels of liquidity

H1: The positive relation between bank liquidity risk and liquidity holdings is less (more) pronounced for banks headquartered in high (low) social capital counties

The effect of social capital on bank liquidity holdings may be impacted by two channels. First, the effect of social capital on bank liquidity holdings may be implicated by the external financing constraints of banks. Firms may face higher costs of external financing and borrowing constraints in the presence of asymmetric information (Myers and Majluf, 1984). Thus, the precautionary motive for hoarding liquidity is expected to be stronger for banks with higher costs of external financing. It is widely recognised that small banks face more borrowing constraints and higher costs of external financing than large banks. Therefore, to the extent that social capital can mitigate the precautionary liquidity holding motives of banks, this effect should be more pronounced for small banks than large banks. Second, the effect of social capital on bank liquidity holdings may be impacted by the moral hazard problems of banks that are deemed to be "too-big-to-fail". Government support for banks may serve as incentive for moral hazard (Mailath and Mester, 1994; Acharya and Yorulmazer, 2007; Gale and Yorulmazer, 2013), which in turn would affect the precautionary motive of banks for liquidity holdings. For example, government support of banking firms in distress may incentivize banks to take on excessive risk, engage in risk shifting, and fund/finance their activities with lower levels of liquidity than they would do otherwise. The precautionary motive for holding liquidity should be stronger for banks with less severe moral hazard problems. It is expected that moral hazard behaviour applies more strongly to large banks than to small banks since large banks are deemed to be "too-big-to-fail" and, in the event of distress, tend to receive government support. Therefore, if social capital can mitigate the precautionary motive of banks for liquidity holdings, then the effect should be more pronounced for small banks with less severe moral hazard problems. This leads to the following hypothesis:

H2: The inverse relation between social capital and bank liquidity holdings is stronger for small banks than large banks

Prior literature shows that social capital is negatively associated with opportunistic behaviour such as corruption (La Porta, Shleifer and Vishny, 1997) and crime (Buonanno, Montolio and Vanin, 2009). I argue that social capital that induces cooperative and altruistic behaviour within a social network can play a role in deterring managerial opportunistic behaviour (e.g., excessive risk taking behaviour) as well as limiting bank borrowers' inclination for opportunistic actions. Moreover, Vazquez and Federico (2015) found that the likelihood of bank failure increases with bank risk-taking. Therefore, banks that are located in high social capital counties have higher probability of survival (Ostergaard, Schindele and Vale, 2016; Jin, Kanagaretnam, Lobo and Mathieu, 2017). The lower likelihood of bank failure would in turn discourage precautionary liquidity holdings by banks.

In particular, three key points are noted. First, opportunistic behaviour violates the social norm and the involved managers are then viewed negatively. Conversely, if managers don't engage in opportunistic behaviour, they are deemed trustworthy and have high reputational capital. Local social norms can be influential, affecting individuals' decisions and behaviour (Cialdini, Kallgren and Reno, 1991), and also constrain narrow self-serving behavior (Knack and Keefer, 1997). The sociological literature generally contends that individuals develop a set of standards of proper behaviour from their surroundings. When individuals make decisions, they avoid deviations from the unwritten set of ethical rules or norms because of internal (e.g., guilt) and external (e.g., shame and ostracism) penalties (Knack and Keefer, 1997). Managers may take civic norms of social peers in the communities surrounding bank headquarters into account when making decisions and behave in a way that conforms to the prescribed civic norms and the expectations of their social peers in the communities (Hasan, Hoi, Wu and Zhang, 2017a). The social norms of high social capital regions induce managers to behave more honestly and restrain managers by disciplining their opportunistic behaviour (e.g., excessive risk-taking and risk shifting). Second, information in a social network circulates/diffuses very quickly (e.g., cultural transmission of values and beliefs) and reputations are built very rapidly about the reliability of people. Social networks are the media through which social capital is created, maintained and used (Ferris, Javakhadze and Rajkovic, 2017). There is a strong solidarity that unites members of the social networks. More frequent interactions among individuals lead to greater information exchange and therefore more effective monitoring (Wu, 2008). The dense networks in high social capital regions increase the reputational costs of opportunistic behaviour and encourage consistent trustworthy and reliable behaviour from managers, i.e., reputation effect created by several repeated social interactions. Since reputation is important for the careers of managers, the loss of reputation will impair their public image and adversely impact the future job prospects of the managers. This serves as incentive to bank managers to avoid shame and social exclusion arising from opportunistic behaviour. Third, borrowers in high social capital counties behave less opportunistically and act less in their self-interest. To the extent that these characteristics reduce moral hazard problems (i.e., credit risk) facing lenders, Hasan, Hoi, Wu and Zhang (2017b) found that borrowers in high social capital counties enjoy a lower spread on their loans because the risks that lenders face and the associated costs are lower. In other words, borrowers have a greater propensity to honor an obligation (e.g., repay bank loan principal and interest when they fall due). Overall, banks that are located in high social capital counties are less exposed to opportunistic behaviour and have lower probability of bank failure, therefore, they are expected to hold lower levels of precautionary liquidity. This leads to the following hypothesis:

H3: The inverse relation between social capital and bank liquidity holdings is more (less) pronounced for low (high) risk taking banks

4.3 Data collection, sample construction and measurement of variables

4.3.1 Sample selection and data source

Bank headquarter location information (state and county) and quarterly financial data are sourced from Statistics on Depository Institutions (SDI) reports of the Federal Deposit Insurance Corporation (FDIC) bank data and statistics. The sample of banks in this paper consists of all the FDIC insured U.S. financial institutions spanning the period of 2003:Q1 to 2014:Q4 with 295,520 bank-quarter observations. The 2003-2014 time period is unique since it contains data before, during and after the largest financial crisis in recent history. On September 15, 2008, a significant, but relatively mild, financial disruption was transformed into a full-fledged financial crisis with the Lehman bankruptcy that led to a large increase in uncertainty and a wave of distressed selling of securities that caused a collapse in asset prices. However, with the implementation of conventional and unconventional monetary policies, and the bailouts of some banks and financial institutions by the U.S. Federal Reserve and Treasury, financial markets began to recover in the first half of 2009. For example, the "TED spread"[34] began to fall from its peak of over 400 basis points (bps) in October 2008 to below 100 bps in January 2009. This spread fell to below pre-crisis levels (less than 20 bps) by May 2009. Therefore, I begin the sample period in 2003 (five years before the GFC) and end it in 2014 (five years after the GFC) to allow for the long-term effect of this exogenous shock on the relation between social capital and bank liquidity holdings. I use the state and county name of each bank's headquarter location each year to match bank data with social capital data and county-level demographic data. In order to mitigate the possible effects from outliers, I winsorize all of the continuous variables of the sample at the 1st and the 99th percentile.

4.3.2 Main variables

4.3.2.1 Measuring social capital

A primary limitation of the social capital concept is the lack of consensus on its definition and its meaning. Because it is difficult to disentangle the norm and network aspects of social capital, I do not make this distinction; instead, I focus on the common aspects of both the norms and the network views. Following Woolcock (2001), I define social capital (*sc*) as norms and networks that facilitate collective action. The underlying data used to estimate the levels of social capital across U.S. counties are available from the Northeast Regional Center for Rural Development (NRCRD) at the Pennsylvania State University. The social capital index for each county is estimated for the years 1997, 2005, and 2009. Following Li, Tang and Jaggi (2016), I linearly interpolate values to fill the missing years from 1998 to 2004 and

[34] The "TED spread" is the spread between the interest rate on interbank lending (as measured by the LIBOR interest rate on three-month Eurodollar deposits) and the interest rate on three-month U.S. Treasury bills. The TED spread provides an assessment of counterparty risk from one bank lending to another, reflecting both liquidity and credit risk concerns.

2006 to 2008. I then linearly extrapolate values for years 2010 to 2014.[35] The social capital index is constructed following Rupasingha, Goetz and Freshwater (2006). They use two measures of norms and two measures of networks to develop a proxy for social capital. The two measures of norms are voter turnout (PVOTE) and census response rates (RESPN). The two measures of networks are the number of social associations (ASSN), including religious organizations, civic and social associations, business associations, political organizations, professional organizations, labor organizations, bowling centers, physical fitness facilities, public golf courses, sport clubs, managers, and promoters, and the total number of tax-exempt non-profit organizations in a county (NCCS). A principal component analysis (PCA) is used to construct a county-level social capital index, which is the first principal component from the PCA based on PVOTE, RESPN, NCCS, and ASSN and captures most of their common variance. Appendix 4.1 describes the NRCRD data.

4.3.2.2 Measuring bank liquidity holdings

Bank liquidity holdings (*liqhod)* are defined as the sum of all cash and balances due from other financial institutions, fed funds sold less fed funds bought, and securities purchased under resale agreements less securities sold under repurchase agreements, scaled by total assets.

4.3.2.3 Measuring control variables

4.3.2.3.1 Bank-specific characteristics

Following the previous literature, I use the CAMELS rating system to assess overall bank financial conditions. In particular, the following control variables are selected from the CAMELS rating system: the ratio of total equity capital to total risk-weighted assets as a proxy of capital adequacy (*ca*); the ratio of all nonperforming loans to total assets as a proxy of asset quality (*aq*); cost-to-income ratio as a proxy of

[35] Alternatively, I fill in the data for the missing years using the social capital measure in the preceding year in which data are available. For example, I fill in missing data from 2006 to 2008 using the social capital measure in 2005. The results remain qualitatively unchanged.

management capability (*mc*); the ratio of net income to total assets as a proxy of earnings (*earn*); and loans-to-deposits ratio as a sensitivity measure to market risk (*ltdrt*).

Furthermore, I control for liquidity risk measured as the ratio of unused loan commitments to total loans (*ucrt*); income diversification measured as the ratio of non-interest income to total income (*noniirt*); bank size measured as the natural logarithm of total assets (*banksize*); bank holding company status (*bhc*); bank liquidity creation, proxied by the preferred liquidity creation measure (*catfat_gta*)[36] of Berger and Bouwman (2009) and z-score, defined as a bank's return on assets (ROA) plus the capital ratio divided by the standard deviation of ROA over the previous twelve quarters. I control for liquidity risk because it may affect liquidity holdings (e.g, Cornett, McNutt, Strahan and Tehranian, 2011; Hong, Huang and Wu, 2014). I control for bank size because liquidity holdings may vary by bank size. For example, small banks are expected to have stronger incentives of holding liquidity than large banks to avoid financing constraints and costly default (Allen, Peristiani and Saunders, 1989). I control for bank holding company (BHC) status because the same BHC may provide capital/liquidity to its different subsidiaries (Houston and James, 1998; Berger and Bouwman, 2009). I include bank liquidity creation as a control variable since the creation of liquidity decreases the liquidity buffer of the bank (Berger and Bouwman, 2009). Finally, z-score is a widely used measure for a bank's risk taking (Duchin and Sosyura, 2014; Jin, Kanagaretnam, Lobo and Mathieu, 2017). This score approximates the inverse of the default probability, with a higher z-score indicating less risk-taking (i.e., more bank stability).

4.3.2.3.2 Macroeconomic and demographic variables

Loan demand depends on regional and nation-wide economic conditions as well as individual bank conditions. To control for varying levels of loan demand, this study employs the Senior Loan Officer Opinion Survey on Bank Lending Practices

[36] BB measure is a comprehensive single measure of bank liquidity since it considers all the on-balance sheet and off-balance sheet activities of banks. I am grateful to Christa Bouwman for providing the bank liquidity creation data. It is downloadable from Christa Bouwman's personal website (https://sites.google.com/a/tamu.edu/bouwman/data).

(*sloos*), which is obtained from the Federal Reserve System.[37] Moreover, this study employs "the slope of the yield curve", measured as the difference between long-term interest rates (10 year Treasury yield) and short-term interest rates (3 month Treasury yield), as a predictor of future real economic activity, which is obtained from the Federal Reserve Bank of New York.[38] Finally, county-level demographic data (e.g., per capita personal income and total employment) are sourced from the Bureau of Economic Analysis (BEA). I also control for the recent financial crisis period, proxied by *crisisdummy*. This variable has a value of one from the third quarter of 2007 to the fourth quarter of 2009, and zero otherwise. The definitions and abbreviations used for the main variables are contained in Appendix 4.2.

4.3.3 Descriptive statistics

Table 4.1 presents summary statistics for the main variables and preliminary results. Panel A of Table 4.1 shows that the average bank liquidity holdings (*liqhod*) is 0.082. The mean (median) value of social capital (*sc*) is -0.115 (-0.257) with an interquartile range of -0.940 to 0.510. The mean value of capital adequacy (*ca*) and asset quality (*aq*) suggest that the sample banks have strong capital position, but low quality of assets.

Consistent with my hypotheses, the univariate results in Panel B of Table 4.1 suggest that the level of social capital where the bank is headquartered is negatively associated with bank liquidity holdings. I divide the sample into high and low social capital groups based on the median level of social capital and compare the average bank liquidity holdings between banks headquartered in high and low social capital counties. Panel B shows that the mean *liqhod* for banks in high social capital counties is 0.074 but it is 0.090 in the low social capital counties, and the difference (0.016) is statistically significant at the 1% level of significance. This result confirms the Hypothesis that social capital can unlock inefficiently high levels of liquidity holdings.

[37] https://www.federalreserve.gov/datadownload/Choose.aspx?rel=SLOOS.
[38] https://www.newyorkfed.org/research/capital_markets/ycfaq.html.

Panel C of Table 4.1 contains the Pearson correlation matrix between the variables of interest. The correlation coefficients are consistent with my predictions. Specifically, social capital (*sc*) is negatively associated with bank liquidity holdings (*liqhod*), which provides preliminary evidence supporting the Hypothesis.

Table 4.1 Descriptive statistics and preliminary results

Panel A:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	N	mean	sd	min	p25	median	p75	max
liqhod	295,520	0.082	0.086	-0.097	0.028	0.065	0.119	0.411
sc	295,520	-0.115	1.171	-2.284	-0.940	-0.257	0.510	3.598
catfat_gta	295,520	0.311	0.178	-0.155	0.196	0.322	0.435	0.718
ca	295,520	0.165	0.074	0.069	0.117	0.145	0.188	0.507
earn	295,520	0.049	0.075	-0.310	0.022	0.048	0.086	0.228
aq	295,520	0.234	0.267	0.000	0.069	0.152	0.294	1.554
mc	295,479	0.783	0.168	0.479	0.689	0.761	0.841	1.629
ltdrt	295,520	0.772	0.201	0.242	0.645	0.788	0.910	1.262
ucrt	295,520	0.166	0.114	0.001	0.087	0.142	0.216	0.658
noniirt	295,390	0.849	1.726	-4.981	0.290	0.578	1.039	11.240
bhc	295,520	0.843	0.364	0.000	1.000	1.000	1.000	1.000
banksize	295,520	11.980	1.185	10.090	11.150	11.810	12.590	16.370
sloos	295,520	0.004	0.253	-0.604	-0.167	0.014	0.196	0.455
spread	295,520	2.036	1.140	-0.512	1.529	2.249	2.875	3.578
lnperinc	295,421	10.450	0.264	9.898	10.270	10.430	10.610	11.240
lnemploy	295,421	10.670	1.925	7.347	9.197	10.210	12.090	15.500
crisisdummy	295,520	0.258	0.438	0.000	0.000	0.000	1.000	1.000

Panel B: VARIABLES	*sc*>=median	*sc*<median	mean difference	t-statistics for equal means
liqhod	0.074	0.090	0.016***	48.639

Panel C: Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1)liqhod	1.00																
(2)catfat_gta	-0.24	1.00															
(3)sc	**-0.09*****	-0.03***	1.00														
(4)ca	0.30***	-0.61***	-0.01***	1.00													
(5)aq	0.04***	0.07***	-0.10***	-0.17***	1.00												
(6)earn	-0.17***	0.01***	0.12***	-0.01***	-0.39***	1.00											
(7)mc	0.21***	-0.06***	-0.11***	0.06***	0.30***	-0.73***	1.00										
(8)ltdrt	0.39***	0.71***	-0.01***	-0.46***	0.12***	-0.01***	-0.02***	1.00									
(9)ucrt	-0.08***	0.41***	0.02***	-0.07***	-0.24***	0.02***	-0.03***	0.10***	1.00								
(10)noniirt	0.01***	0.03***	-0.05***	-0.03***	-0.02***	0.05***	0.00*	-0.01***	0.06***	1.00							
(11)banksize	-0.31***	0.34***	-0.23***	-0.22***	0.04***	0.05***	-0.19***	0.23***	0.35***	0.09***	1.00						
(12)crisisdummy	-0.08***	0.03***	-0.00	-0.04***	0.06***	-0.12***	0.17***	0.14***	0.01***	-0.02***	0.01**	1.00					
(13)lnperinc	0.06***	0.26***	0.12***	-0.04***	0.04***	-0.14***	0.10***	0.09***	0.27***	0.02***	0.26***	0.04***	1.00				
(14)lnemploy	0.01***	0.32***	-0.41***	-0.10***	0.08***	-0.21***	0.20***	0.23***	0.27***	0.06***	0.40***	0.02***	0.52***	1.00			
(15)spread	0.08***	-0.05***	-0.03***	0.00	0.18***	-0.13***	0.01***	-0.07***	-0.11***	0.02***	0.02***	-0.04***	0.05***	-0.01***	1.00		
(16)sloos	0.00	0.02***	0.00	0.03***	-0.11***	0.10***	-0.13***	-0.07***	0.04***	0.00	0.01**	-0.58***	0.04***	-0.01***	-0.22***	1.00	
(17)bhc	-0.17***	0.12***	0.10***	-0.21***	0.01**	0.13***	-0.16***	0.07***	0.04***	0.03***	0.18***	0.00	-0.06***	-0.11***	0.00	0.00	1.00

Note: There are three panels in this table. Panel A shows the summary statistics for key variables. Panel B presents univariate test results on means based on the median level of social capital. Panel C reports Pearson correlation matrix between variables. Full definitions of all variables are presented in Appendix 4.2. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

4.4 Econometric models

In order to investigate the association between the social capital of a county in which a bank is headquartered and bank liquidity holdings, the following baseline OLS regression model is applied:

$$
\begin{aligned}
&liqhod \\
&= \beta_0 + \beta_1 sc + \beta_2 ca + \beta_3 aq + \beta_4 earn + \beta_5 catfat\_gta + \beta_6 banksize + \beta_7 bhc \\
&+ \beta_8 crisisdummy + \beta_9 lnperinc + \beta_{10} lnemploy + \beta_{11} spread + \beta_{12} sloos \\
&+ \Sigma Time, State\ and\ Bank\ Fixed\ Effects \\
&+ \varepsilon \qquad (1)
\end{aligned}
$$

In Eq. (1), the dependent variable is bank liquidity holdings (*liqhod)*, defined as the sum of all cash and balances due from other financial institutions, fed funds sold less fed funds bought, and securities purchased under resale agreements less securities sold under repurchase agreements, scaled by total assets. The key variable of interest is the social capital of the county where the bank is headquartered (*sc*). I expect the coefficient on social capital, β_1, to be negative and significant, indicating that high social capital is associated with lower levels of liquidity holdings since banks located in high social capital regions are expected to have lower liquidity risk and less external financial constraints. I also control for bank-specific characteristics, macroeconomic and county-level demographic conditions; and ε is a random error term. Please note that Eq. (1) is only the baseline model; liquidity risk variable (*ucrt*) will be added in the baseline regression model to interact with the key independent variable (*sc*) to test H1, and bank risk taking variable (*z_score*) will be added in the baseline regression model to interact with the key independent variable (*sc*) to test H3. All control variables are discussed in detail in Section 4.3.2.3.

I estimate Eq. (1) with the Ordinary Least Squares (OLS) method in four different ways: without any fixed effects, and respectively with year-quarter fixed effects, with state fixed effects, and with bank fixed effects. Fixed effects account for differences in time, states and banks. The inclusion of year-quarter fixed effects captures factors specific to individual year-quarters. I include state fixed effects to control for the influences of unknown time-invariant state-level factors. Justification for the inclusion of bank fixed effects is derived from the argument that there are unobserved, time-invariant bank-level heterogeneity, such as culture and governance.

4.5 Empirical results

4.5.1 Test of the main hypothesis

Table 4.2 presents estimates of the baseline model using OLS regressions with standard errors clustered at bank level.[39] The overall fit of the regression models is satisfactory and the variance inflation factor[40] shows no problems with regards to multicollinearity. The estimates of *sc* across all specifications are negative and significant. For example, Model 7 shows that social capital has a negative effect on the liquidity holdings of banks, based on the results that the estimated coefficient of *sc* is -0.003 and is statistically significant at the 1% level of significance.[41] In terms of economic significance, Model 1 shows that one standard deviation increase in the *sc* is associated with a 0.16 standard deviation decrease in the *lidhod* (-0.012*1.171/0.086). This coefficient also indicates that a bank headquartered in a county with social capital in the 75th percentile holds 1.72% less (i.e., 1-(exp(-0.012*0.51)/exp(-0.012*-0.94))) in *liqhod* than a bank headquartered in a county with social capital in the 25th percentile, ceteris paribus. These results provide support for the Hypothesis and show that bank liquidity holdings are negatively associated with social capital.

Turning to the control variables across the different specifications, the results are generally consistent with my prediction. In terms of the CAMELS rating, I find

[39] Following Jha and Chen (2015), and Jha and Cox (2015), I also cluster the standard errors at the county level to adjust for a possible correlation in the error term that is related to county characteristics. The result is qualitatively similar.
[40] The highest VIF is 2.24 related to county-level employment variable (*lnemploy*) and the mean of all the VIFs is 1.56.
[41] As a robustness check, I also use the ratio of cash and balances due from depository institutions to total assets as a proxy for bank liquidity holdings and find similar results.

that bank equity capital (*ca*) has a statistically significant positive relationship with bank liquidity holdings. It indicates that liquidity buffers and capital cushions are positively correlated. I find mixed evidence on the effect of asset quality (*aq*) on bank liquidity holdings. This is not surprising given that on the one hand banks with more non-performing assets may hold more liquidity for self-insurance purposes, whilst on the other hand, large proportions of non-performing assets may deplete the liquidity buffers of banks. The negative coefficient of profitability (*earn*) suggests that there is a trade-off between liquidity buffers and profitability. In other words, liquid assets are costly because they earn low returns. I find that bank liquidity creation (*catfat_gta*) is significantly negatively related to bank liquidity holdings because liquidity creation makes banks less liquid (Berger and Bouwman, 2009). The coefficient of *banksize*, as expected, reflects that large banks are less likely to hoard cash either because they can more easily access funding from national or international capital markets or due to their "too-big-to-fail" positions. The coefficient of *bhc* is negative and significant in most of the specifications, indicating that bank holding companies are less likely to hoard liquidity because they could depend on internal capital markets to provide capital and liquidity (Houston and James, 1998). Furthermore, I find that the effects of macroeconomic and county-level demographic variables (*crisisdummy, lnperinc, lnemploy, spread* and *sloos*) on bank liquidity holdings vary, indicating that banks hold more cash during good economic time periods as liquidity buffer against future economic shocks; on the other hand, as Acharya, Shin and Yorulmazer (2011) suggest, liquidity hoarding is countercyclical – lower during economic upturns and higher when recessions approach.

Table 4.2 Baseline OLS regression

VARIABLES	(1) *lidhod*	(2) *lidhod*	(3) *lidhod*	(4) *lidhod*	(5) *lidhod*	(6) *lidhod*	(7) *lidhod*
sc	**-0.012*** **	**-0.009*** **	**-0.008*** **	**-0.003*** **	**-0.006*** **	**-0.003*** **	**-0.003*** **
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ca	0.216***	0.202***	0.172***	0.155***	0.094***	0.065***	0.066***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
aq	0.008***	-0.001	0.009***	-0.000	-0.003**	-0.012***	-0.012***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
earn	-0.113***	-0.115***	-0.117***	-0.119***	-0.098***	-0.101***	-0.101***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
catfat_gta	-0.028***	-0.027***	-0.051***	-0.050***	-0.223***	-0.220***	-0.221***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
banksize	-0.024***	-0.025***	-0.023***	-0.025***	-0.014***	-0.023***	-0.023***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
bhc	-0.006***	-0.007***	-0.001	-0.001	-0.005**	-0.007***	-0.007***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
crisisdummy	-0.023***	0.015***	-0.023***	0.021***	-0.022***	0.034***	0.033***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lnperinc	0.058***	0.029***	0.058***	0.021***	0.099***	0.033***	0.034***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
lnemploy	-0.000	0.003***	-0.001**	0.002***	-0.004*	0.003	0.003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
spread	0.003***	-0.022***	0.003***	-0.027***	0.001***	-0.033***	-0.033***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
sloos	-0.019***	-0.007**	-0.017***	0.003	-0.018***	0.017***	0.017***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-0.258***	0.091**	-0.252***	0.192***	-0.679***	0.148**	0.102
	(0.03)	(0.05)	(0.03)	(0.04)	(0.03)	(0.06)	(0.06)
Year_quarter FE	No	Yes	No	Yes	No	Yes	Yes
State FE	No	No	Yes	Yes	No	No	Yes
Bank FE	No	No	No	No	Yes	Yes	Yes
Observations	295,421	295,421	295,421	295,421	295,421	295,421	295,421
R-squared	0.231	0.247	0.279	0.309	0.689	0.697	0.698

Note: This table presents the multivariate OLS regression analysing Eq. (1) on the relationship between the social capital of a county in which a bank is headquartered (*sc*) and liquidity holdings of the bank (*liqhod*). The variable descriptions are in Appendix 4.2. Regressions include different Fixed Effects (FE) estimations (Year_quarter FE, State FE and Bank FE) across Model (2)-(7). Robust standard errors clustered by bank are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

4.5.2 Test of H1

To test H1, I analyse the effect of social capital on the relation between liquidity risk (*ucrt*) and liquidity holdings. Cornett, McNutt, Strahan and Tehranian (2011) found that banks with higher liquidity risk increase their holdings of liquid assets (i.e., their precautionary demand for liquidity increases). Following their study, I use the ratio of unused loan commitments to total loans as a proxy for liquidity risk, which is interacted with the measure of social capital to assess the moderating effect of social capital on the relation between liquidity risk and liquidity holdings. I expect that the positive relation between liquidity risk and liquidity holdings is less pronounced for banks headquartered in high social capital regions. I replicate Eq. (1) in the full sample by adding the interaction term *sc*×*ucrt*.

As shown in Table 4.3, the coefficients of *ucrt* are positive and statistically significant, suggesting that banks with higher liquidity risk tend to hold more precautionary liquidity for self-insurance purposes. The coefficients of *sc* preserve the negative sign and are still statistically significant, indicating that banks with headquarters located in high social capital counties hold less liquidity. In Model (1)-(3) where no fixed effects are included or only Year-quarter or State fixed effects is included, the coefficients of *sc*×*ucrt* are negative and significant, indicating that for banks with headquarters that located in high social capital counties, liquidity risk is negatively related to bank liquidity holdings. In Model (4) where I control for all fixed effects (Year_quarter, State and Bank FE), the coefficient of *sc*×*ucrt* is insignificant, implying that liquidity holdings are less sensitive to liquidity risk for banks with greater social capital. I view these findings as supportive of my expectation that social capital has a moderating effect on the relation between liquidity risk and liquidity holdings. The possible explanation is that social capital might provide banks with assurance of safety (e.g., social network may reduce the moral hazard (Ferrary, 2003), and trust and civic norms may facilitate the enforcement of contracts (Knack and Keefer, 1997)). Thus banks would have weak precautionary motive for holding liquidity. The total *ucrt* coefficient is the sum of the *ucrt* coefficient estimate and the coefficient estimate of the interaction term *sc*×*ucrt*. The coefficient estimates of the interaction terms appear to be economically significant. For example, the total overall effect of liquidity risk on liquidity holdings in the 25th percentile of *sc* in Column (1) of Table 4.3, is at least 1.61 times larger than the same indicator in the 75th percentile.[42]

Table 4.3 How does the social capital affect the relation between bank liquidity risk and liquidity holdings?

VARIABLES	(1) *liqhod*	(2) *liqhod*	(3) *liqhod*	(4) *liqhod*
sc	**-0.010*** **	**-0.006*** **	**-0.005*** **	**-0.002* **
	(0.00)	(0.00)	(0.00)	(0.00)
ucrt	**0.052*** **	**0.066*** **	**0.066*** **	**0.116*** **
	(0.01)	(0.01)	(0.01)	(0.01)
sc*ucrt	**-0.018*** **	**-0.019*** **	**-0.017*** **	**-0.002**
	(0.01)	(0.01)	(0.01)	(0.00)
ca	0.197***	0.176***	0.157***	0.028***
	(0.01)	(0.01)	(0.01)	(0.01)
aq	0.015***	0.007***	0.008***	-0.004**
	(0.00)	(0.00)	(0.00)	(0.00)
earn	-0.104***	-0.104***	-0.118***	-0.093***
	(0.01)	(0.01)	(0.01)	(0.00)
catfat_gta	-0.044***	-0.047***	-0.053***	-0.246***
	(0.01)	(0.01)	(0.01)	(0.01)
banksize	-0.025***	-0.026***	-0.026***	-0.022***
	(0.00)	(0.00)	(0.00)	(0.00)
bhc	-0.006***	-0.007***	-0.008***	-0.006**
	(0.00)	(0.00)	(0.00)	(0.00)
crisisdummy	-0.023***	0.020***	0.023***	0.040***
	(0.00)	(0.00)	(0.00)	(0.00)
lnperinc	0.057***	0.025***	0.020***	0.022***
	(0.00)	(0.00)	(0.00)	(0.01)
lnemploy	-0.000	0.003***	0.003***	0.003
	(0.00)	(0.00)	(0.00)	(0.00)
spread	0.003***	-0.024***	-0.027***	-0.036***
	(0.00)	(0.00)	(0.00)	(0.00)
sloos	-0.018***	-0.002	0.002	0.024***
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-0.232***	0.165***	0.203***	0.185***
	(0.03)	(0.05)	(0.04)	(0.06)
Year_quarter FE	No	Yes	No	Yes
State FE	No	No	Yes	Yes
Bank FE	No	No	No	Yes
Observations	295,421	295,421	295,421	295,421
R-squared	0.235	0.253	0.283	0.703

Note: This table presents the moderating effect of social capital on the relationship between liquidity risk and bank liquidity holdings by adding the interaction term *sc*×*ucrt* in Eq. (1). *ucrt* denotes the liquidity risk, measured as the ratio of unused loan commitments to total loans. The variable descriptions are in Appendix 4.2. Robust standard errors clustered by bank are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

[42] [(-0.94)*(-0.018)+0.052]/[0.51*(-0.018)+0.052]=1.61

4.5.3 Test of H2

To test H2, I divide the full sample into large and small banks based on the median level of the natural logarithm of total assets.[43] It is widely recognised that small banks/firms face more borrowing constraints and higher costs of external financing than large banks/firms. Specifically, I expect that social capital is significant in reducing inefficiently high levels of liquidity holdings for financially constrained small banks. Conversely, social capital is less important for financially unconstrained large banks that enjoy ready access to external financing. In addition, it is expected that the moral hazard behaviour applies more to large banks than to small banks since large banks are deemed to be "too-big-to-fail" and, in the event of distress, tend to receive government support. It is well-documented that both systemic bank risk and bank risk taking increase with bank size (Laeven, Ratnovski and Tong, 2016; De Jonghe, Diepstraten and Schepens, 2015; Bhagat, Bolton and Lu, 2015). Specifically, large banks are more likely to engage in excessive risk taking and tend to hold lower levels of liquidity than small banks. Thus, if social capital can alleviate the high levels of bank liquidity holdings, the effect should be more pronounced for small banks because they have stronger precautionary motive and less severe moral hazard problems than large banks.

Column (1) of Table 4.4 reports the baseline estimates restricted to the sample of large banks (with the natural logarithm of total assets above the 50th percentile of the distribution) and Column (2) for the sample of small banks (with the natural logarithm of total assets below or equal to the 50th percentile of the distribution). As expected, in the "large bank" sub-sample, the coefficient for *sc* is small (-0.001) and statistically insignificant, whereas in the "small bank" sub-sample, the coefficient for *sc* is large (-0.005) and statistically significant at 1% level. More importantly, the test of coefficient differences for the two samples also reveals that the magnitudes of the coefficients are significantly different from each other as indicated by the F test. In terms of economic significance, large banks located in a county with social capital in

[43] Following banking literature (e.g., Kashyap and Stein, 2000), I define banks as small if the asset size of the bank is below the 95th percentile in the asset distribution of all banks and as large if the asset size is above the 99th percentile. I find that the coefficient of *sc* for small banks is negative at the 1% significance level, while it is statistically insignificant for large banks.

the 75th percentile hold 0.14% less in liquidity than large banks located in a county with social capital in the 25th percentile.[44] Small banks located in a county with social capital in the 75th percentile hold 0.72% less in liquidity than small banks located in a county with social capital in the 25th percentile.[45] This represents a difference of more than four times (i.e., -4.14 = (0.14 – 0.72)/0.14) between large banks and small banks.

Table 4.4 The effect of social capital on bank liquidity holdings for different sizes of banks

	(1) large banks	(2) small banks
VARIABLES	*liqhod*	*liqhod*
sc	**-0.001**	**-0.005*****
	(0.00)	(0.00)
ca	0.044**	0.027*
	(0.02)	(0.01)
aq	-0.002	-0.019***
	(0.00)	(0.00)
earn	-0.069***	-0.101***
	(0.01)	(0.01)
catfat_gta	-0.175***	-0.300***
	(0.01)	(0.01)
banksize	-0.017***	-0.023***
	(0.00)	(0.00)
bhc	-0.008**	-0.008**
	(0.00)	(0.00)
crisisdummy	0.039***	0.039***
	(0.00)	(0.00)
lnperinc	-0.008	0.048***
	(0.01)	(0.01)
lnemploy	-0.002	0.002
	(0.00)	(0.00)
spread	-0.033***	-0.038***
	(0.00)	(0.00)
sloos	0.036***	0.011**
	(0.01)	(0.01)
Constant	0.566***	0.027
	(0.09)	(0.09)
Year_quarter FE	Yes	Yes
State FE	Yes	Yes
Bank FE	Yes	Yes
Test for difference of the coefficient of *sc* across two subsamples	F value=24.94, *p*-value=0.000	
Observations	147,759	147,662
R-squared	0.6944	0.7031

Note: This table reports the results of H2 using the baseline OLS regression model in Eq. (1). I separate the full sample into two subsamples: large banks (with the natural logarithm of total assets above the median level of the distribution) and small banks (with the natural logarithm of total assets below or equal to the median level of the distribution). The variable descriptions are in Appendix 4.2. Robust standard errors clustered by bank are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

[44] 1-(exp(-0.001*0.51)/exp(-0.001*-0.94))=0.14%

[45] 1-(exp(-0.005*0.51)/exp(-0.005*-0.94))=0.72%

4.5.4 Test of H3

To test H3, I analyse how the effect of social capital on bank liquidity holdings varies with bank risk-taking behaviour. Jin, Kanagaretnam, Lobo and Mathieu (2017) found that social capital is negatively related to bank risk-taking. The lower level of risk-taking would in turn reduce banks' precautionary liquidity holdings. I posit that the relationship between social capital and bank liquidity holdings is stronger for less excessive risk-taking banks, since less risky banks have weaker precautionary motives for holding liquidity. Consistent with the measure of risk-taking in the literature (Jin, Kanagaretnam, Lobo and Mathieu, 2017; Duchin and Sosyura, 2014; Berger and Bouwman, 2009), the z-score that is defined as a bank's return on assets (ROA) plus the capital ratio divided by the standard deviation of ROA over the previous twelve quarters, is interacted with the measure of social capital to assess how the effect of social capital on bank liquidity holdings varies with the level of risk-taking. A higher z-score indicates that a bank is more stable. I expect that the inverse relation between social capital and liquidity holdings is more pronounced for banks that have lower levels of excessive risk-taking. I replicate Eq. (1) in the full sample by adding the interaction term *sc*×*z_score*.

As shown in Table 4.5, the coefficients of *z_score* are negative and statistically significant, suggesting that banks with higher z-score (i.e., more bank stability) tend to hold less precautionary liquidity for self-insurance purposes. The coefficients on *sc* preserve the negative sign and are still statistically significant, indicating that banks with headquarters located in high social capital counties hold less liquidity. As expected, the coefficients of *sc*×*z_score* are negative and statistically significant in all specifications, implying that the negative effect of social capital on liquidity holdings is stronger for high z-score banks (i.e., banks with less excessive risk-taking behaviour). Overall, the findings provide supportive evidence for H3.

Table 4.5 How does the effect of social capital on bank liquidity holdings vary with different levels of bank risk taking?

VARIABLES	(1) *liqhod*	(2) *liqhod*	(3) *liqhod*	(4) *liqhod*	(5) *liqhod*
sc	**-0.0097*****	**-0.0066*****	**-0.0060*****	**-0.0044*****	**-0.0010***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
z_score	**-0.0006*****	**-0.0024*****	**-0.0005*****	**-0.0003*****	**-0.0020*****
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
sc*z_score	**-0.0001****	**-0.0001****	**-0.0001***	**-0.0001*****	**-0.0001*****
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ca	0.2615***	0.3935***	0.2077***	0.1128***	0.2313***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
aq	0.0071***	0.0005	0.0081***	-0.0041***	-0.0134***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
earn	-0.1205***	-0.0871***	-0.1234***	-0.1066***	-0.0818***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
catfat_gta	-0.0216***	0.0028	-0.0459***	-0.2195***	-0.1966***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
banksize	-0.0239***	-0.0252***	-0.0235***	-0.0146***	-0.0244***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
bhc	-0.0066***	-0.0085***	-0.0014	-0.0053**	-0.0068***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
crisisdummy	-0.0225***	-0.0530***	-0.0228***	-0.0215***	-0.0236***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
lnperinc	0.0572***	0.0282***	0.0578***	0.0988***	0.0328***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
lnemploy	-0.0001	0.0030***	-0.0013**	-0.0036*	0.0034
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
spread	0.0027***	0.0171***	0.0026***	0.0012***	-0.0001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
sloos	-0.0177***	-0.0446***	-0.0166***	-0.0173***	-0.0147***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-0.2458***	0.0117	-0.2433***	-0.6689***	0.0381
	(0.03)	(0.05)	(0.03)	(0.03)	(0.06)
Year_quarter FE	No	Yes	No	No	Yes
State FE	No	No	Yes	No	Yes
Bank FE	No	No	No	Yes	Yes
Observations	295,421	295,421	295,421	295,421	295,421
R-squared	0.233	0.255	0.280	0.217	0.246

Note: This table presents how the effect of social capital on bank liquidity holdings varies with the levels of risk-taking by adding the interaction term *sc*×*z_score* in Eq. (1). *z_score* denotes the bank risk-taking behaviour, measured as a bank's return on assets (ROA) plus the capital ratio divided by the standard deviation of ROA over the previous twelve quarters. The variable descriptions are in Appendix 4.2. Robust standard errors clustered by bank are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

4.6 Concerns of endogeneity

Endogeneity concerns may arise from reverse causality (e.g., banks with less liquidity holdings may choose to have their headquarters in high social capital counties) as well as omitted variables bias (note that the use of the fixed effects to control for unobservable characteristics partly but not completely alleviates this concern). To address the endogeneity concerns of social capital in the baseline regressions, an instrumental variable estimation method is applied. I use the state level mean of social capital (*state_sc*) in each year as an instrument for the endogenous variable *sc* to further validate the interpretation of the result. My choice of the instrument variable has ex ante theoretical plausibility. Identification of the IV model requires a strong correlation between the instrument and endogenous variable. It is reasonable to expect that state level social capital is highly correlated with the social capital of the counties located in that particular state. For the instrument to be valid it should not be affected by the dependent variable, and not affect the dependent variable except through the endogenous variable. It is unlikely that the liquidity holding affects the state level social capital. Also it is unlikely that the state level social capital affects bank liquidity holdings except through the social capital of where the bank is headquartered. The statistical tests validate the choice of the instrument and indicate robustness. The Dubin Wu-Hausman's endogeneity test shows that the social capital measure is indeed endogenous. The Kleibergen-Paap Wald rk F statistic shows that the instrument is relevant and do no suffer from weak instrument concerns. I use the Two-Stage Least Square (2SLS) IV approach to address possible endogeneity in my baseline OLS regressions.

The 2SLS IV approach involves estimating the following second-stage structural model using the predicted values from the first-stage instrumental variables equation:

$$\begin{aligned} liqhod &= \beta_0 + \beta_1 \widehat{sc} + \beta_2 ca + \beta_3 aq + \beta_4 earn + \beta_5 catfat\_gta + \beta_6 banksize \\ &+ \beta_7 bhc + \beta_8 crisisdummy + \beta_9 lnperinc + \beta_{10} lnemploy + \beta_{11} spread \\ &+ \beta_{12} sloos + \Sigma Time, State\ and\ Bank\ Fixed\ Effects \\ &+ \varepsilon \end{aligned} \tag{2}$$

First-stage instrumental variables model:

$$sc = \beta_0 + \beta_1 state\_sc + \beta_2 ca + \beta_3 aq + \beta_4 earn + \beta_5 catfat\_gta + \beta_6 banksize + \beta_7 bhc + \beta_8 crisisdummy + \beta_9 lnperinc + \beta_{10} lnemploy + \beta_{11} spread + \beta_{12} sloos + +\Sigma Time, State\ and\ Bank\ Fixed\ Effects + \varepsilon \quad (3)$$

where *state_sc* is the instrumental variable, the mean of the state level social capital in each year; the rest of the variables are defined in Eq. (1). I report the results from the first and the second stage regressions in Table 4.6. As shown in Column (1) of Table 4.6, the coefficient for the instrumental variable, *state_sc*, is both statistically significant and quantitatively large. The negative and statistically significant coefficient of *sc* in Column (2) tends to provide support for the Hypothesis. When I instrument *sc* with *state_sc*, the estimated coefficient of *sc* increases from -0.003 (Column (7) of Table 4.2) to -0.004 and is statistically highly significant. This result suggests that reverse causality is unlikely to be driving the results as in this case the IV regressions should have yielded a lower estimate. It is social capital that is most likely to drive bank liquidity, not the other way around. Overall, the results in this section present strong evidence of a negative relation between social capital and bank liquidity.

Table 4.6 Two-Stage Least Square (2SLS) IV regression of social capital on bank liquidity holdings

	(1) First stage	(2) Second stage
VARIABLES	DV=Social Capital (*sc*)	DV=Bank Liquidity Holdings (*liqhod*)
sc		**-0.004***** (0.00)
state_sc	**1.034***** (0.02)	
ca	0.033 (0.06)	0.066*** (0.01)
earn	-0.071 (0.03)***	-0.101*** (0.00)
banksize	-0.042*** (0.01)	-0.023*** (0.00)
catfat_gta	-0.029 (0.03)	-0.221*** (0.01)
aq	0.029** (0.01)	-0.012*** (0.00)
bhc	-0.017 (0.02)	-0.007*** (0.00)
crisisdummy	-0.040*** (0.01)	0.000 (0.00)
lnperinc	0.454*** (0.06)	0.034*** (0.01)
lnemploy	-0.168*** (0.03)	0.002 (0.00)
spread	-0.017*** (0.00)	0.005*** (0.00)
sloos	-0.206*** (0.04)	0.025*** (0.00)
Constant	-3.334*** (0.66)	0.004 (0.06)
Year_quarter FE	Yes	Yes
State FE	Yes	Yes
Bank FE	Yes	Yes
Observations	295,421	295,421
R-squared	0.444	0.205
Kleibergen-Paap Wald rk F statistic	F-stat= 5035.78, *p*-value=0.000	
Endogeneity test	Chi-stat= 2726.96, *p*-value=0.000	

Note: This table reports the results of Two-Stage Least Squares (2SLS) regression analysis estimating Eq. (2) and (3) to test the association between social capital and bank liquidity holdings. In Column (1), the first-stage estimation of Eq. (3) is presented, using the state level mean social capital (*state_sc*) in each year as the instrument to obtain the predicted value of social capital. In Column (2), the estimation of Eq. (2) is presented, using the predicted value of social capital from the first-stage to estimate the relationship between social capital and bank liquidity holdings. The variable descriptions are in Appendix 4.2. Robust standard errors clustered by bank are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

4.7 Additional test

4.7.1 Cross sectional analysis

Following Hilary and Hui (2009) and Jha and Cox (2015), I conduct cross-sectional regressions at the county and year-quarter level to address the concern that the observations may be clustered in a limited number of counties and remove the temporal variations. To do so, I calculate the average values of the different variables[46] based on both county and year-quarter over the entire sample period (2003:Q1 to 2014:Q4) and re-run the regressions treating each county and year-quarter as one observation. Although the sample size decreases to 64,852 observations, the coefficient of *sc* continues to be significant at the 1% level of significance. I also take the average values of all of the variables for each bank. Therefore, only one observation per bank remains and then I conduct the regression analysis. The sample size drops to 8,051 observations, the coefficient of *sc* hardly changes and continues to be significant at the 1% level of significance. Thus, the significant relation between social capital and bank liquidity holdings does not appear to be driven by the large sample size. Table 4.7 presents these results.

[46] I remove dummy variables, such as "*crisisdummy*" and "*bhc*" since the value of dummy variables cannot be averaged.

Table 4.7 Cross sectional analysis

	(1)	(2)
	county and year_quarter level	bank level
VARIABLES	*liqhod*	*liqhod*
sc	**-0.011*****	**-0.010*****
	(0.00)	(0.00)
ca	0.249***	0.259***
	(0.01)	(0.01)
aq	0.012***	0.003
	(0.00)	(0.00)
earn	-0.110***	-0.094***
	(0.00)	(0.02)
catfat_gta	0.006**	-0.000
	(0.00)	(0.01)
banksize	-0.029***	-0.025***
	(0.00)	(0.00)
lnperinc	0.059***	0.037***
	(0.00)	(0.00)
lnemploy	-0.001***	0.001*
	(0.00)	(0.00)
spread	0.004***	0.020***
	(0.00)	(0.00)
sloos	0.006***	-0.011
	(0.00)	(0.01)
Constant	-0.216***	-0.100**
	(0.01)	(0.04)
Observations	64,852	8,051
R-squared	0.229	0.272

Note: This table reports the cross sectional analysis for testing the Hypothesis. In Column (1), I collapse the data based on the county and year_quarter level, treating each county and year_quarter as one observation. In Column (2), I collapse the data so that each bank only has one observation. This table shows that the results are not driven by the sample size. The variable descriptions are in Appendix 4.2. Robust standard errors clustered by bank are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

4.7.2 Alternative measures of social capital

In order to mitigate the concerns that the results might be biased because of measurement errors associated with the social capital index, I follow Jha and Cox (2015) and use a dichotomous measure instead of a continuous variable. I construct a dummy variable that takes the value of one if the bank is headquartered in a county with more than the median level of social capital, and zero otherwise. The results continue to hold.

Prior literature also use blood or organ donation as an alternative proxy for social capital (e.g., Wu, Firth and Rui, 2014; Guiso, Sapienza and Zingales, 2004; Hasan, Hoi, Wu and Zhang, 2017b; Li, Tang and Jaggi, 2016). Following these literature, I obtain the state-level organ donation data from the Organ Procurement and

Transplantation Network (OPTN) to construct an alternative measure of social capital. Organ donation is defined as the state-level per capital organ donor multiplied by 1,000.[47] I modify the models by replacing social capital (*sc*) with organ donation (*od*). In most cases, the results are fairly robust under this alternative measure of social capital. Table 4.8 presents these results.

[47] State-level per capita organ donor is the total number of organ donors in a state in a given year divided by total state population in that year. Organ donation data can be obtained from the OPTN via the link https://optn.transplant.hrsa.gov/data/view-data-reports/state-data/. State population data can be obtained from the U.S. Bureau of Economic Analysis (BEA).

Table 4.8 Alternative measures of social capital

Panel A: VARIABLES	(1) *liqhod*	(2) *liqhod*	(3) *liqhod*	(4) *lidhod*	(5) *lidhod*	(6) *liqhod*	(7) *lidhod*
sc	**-0.021*****	**-0.016*****	**-0.012*****	**-0.005*****	**-0.006*****	**-0.003****	**-0.003****
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ca	0.219***	0.201***	0.173***	0.155***	0.095***	0.065***	0.066***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
aq	0.009***	-0.001	0.009***	-0.000	-0.003**	-0.013***	-0.013***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
earn	-0.114***	-0.116***	-0.117***	-0.119***	-0.098***	-0.101***	-0.101***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
catfat_gta	-0.032***	-0.029***	-0.052***	-0.050***	-0.222***	-0.220***	-0.221***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
banksize	-0.023***	-0.024***	-0.023***	-0.025***	-0.014***	-0.023***	-0.023***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
bhc	-0.007***	-0.008***	-0.001	-0.001	-0.005**	-0.007***	-0.007***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
crisisdummy	-0.022***	0.020***	-0.023***	0.023***	-0.022***	0.034***	0.034***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lnperinc	0.047***	0.018***	0.053***	0.018***	0.102***	0.033***	0.034***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
lnemploy	0.002***	0.005***	-0.000	0.003***	-0.003*	0.003	0.003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
spread	0.003***	-0.025***	0.003***	-0.028***	0.001***	-0.033***	-0.033***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
sloos	-0.017***	-0.000	-0.017***	0.005*	-0.018***	0.018***	0.018***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-0.161***	0.203***	-0.207***	0.225***	-0.705***	0.148**	0.103*
	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.06)	(0.06)
Year_quarter FE	No	Yes	No	Yes	No	Yes	Yes
State FE	No	No	Yes	Yes	No	No	Yes
Bank FE	No	No	No	No	Yes	Yes	Yes
Observations	295,421	295,421	295,421	295,421	295,421	295,421	295,421
R-squared	0.226	0.245	0.278	0.309	0.688	0.697	0.698

Panel B: VARIABLES	(1) *liqhod*	(2) *liqhod*	(3) *liqhod*	(4) *liqhod*	(5) *liqhod*	(6) *liqhod*	(7) *liqhod*
od	**-1.263*****	**-0.987*****	**-0.870*****	**-0.231*****	**-0.478*****	**-0.170*****	**-0.176*****
	(0.07)	(0.07)	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)
ca	0.214***	0.196***	0.172***	0.154***	0.094***	0.065***	0.066***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
aq	0.011***	0.000	0.010***	-0.000	-0.003**	-0.013***	-0.013***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
earn	-0.114***	-0.114***	-0.118***	-0.119***	-0.099***	-0.101***	-0.101***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
catfat_gta	-0.034***	-0.031***	-0.051***	-0.050***	-0.221***	-0.220***	-0.221***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
banksize	-0.023***	-0.024***	-0.023***	-0.025***	-0.014***	-0.023***	-0.023***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
bhc	-0.007***	-0.008***	-0.001	-0.001	-0.005**	-0.007***	-0.007***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
crisisdummy	-0.022***	0.028***	-0.022***	0.026***	-0.022***	0.035***	0.035***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lnperinc	0.037***	0.009**	0.047***	0.014***	0.100***	0.032***	0.033***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
lnemploy	0.004***	0.006***	0.001*	0.004***	-0.003	0.003	0.003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
spread	0.002***	-0.028***	0.002***	-0.029***	0.001***	-0.034***	-0.033***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
sloos	-0.016***	0.008***	-0.016***	0.009***	-0.018***	0.019***	0.018***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-0.026	0.329***	-0.114***	0.271***	-0.671***	0.161***	0.118*
	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.06)	(0.06)
Year_quarter FE	No	Yes	No	Yes	No	Yes	Yes
State FE	No	No	Yes	Yes	No	No	Yes
Bank FE	No	No	No	No	Yes	Yes	Yes
Observations	295,421	295,421	295,421	295,421	295,421	295,421	295,421
R-squared	0.227	0.246	0.277	0.308	0.689	0.697	0.698

Note: There are two panels in this table. Panel A examines the effect of social capital on bank liquidity holdings. Instead of using the continuous social capital index, I use the indicator variable that is equal to one for banks that have above median social capital and zero for those that have below or equal to median social capital. Panel B presents the effect of social capital on bank liquidity holdings using organ donation as an alternative measure of social capital. Organ donation (*od*) is the state-level per capita organ donor multiplied by 1,000. Full definitions of other variables are presented in Appendix 4.2. Robust standard errors clustered by bank are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

4.8 Conclusion

Social capital, defined as the norms and the networks that facilitate collective action (Woolcock, 2001), has been the subject of several studies but, to my knowledge, the impact of social capital has not been formally addressed in previous empirical studies of bank liquidity holdings, which is the focal point of this study.

Using a large panel of FDIC insured U.S. financial institutions from 1,438 counties for the period 2003:Q1 to 2014:Q4, I find that county-level social capital is an important determinant of bank liquidity holdings along with other conventional factors. I can draw four general conclusions from my analysis. First, a bank headquartered in a high social capital county in the U.S. holds lower levels of liquidity. Second, the effect of social capital on liquidity holdings is more pronounced for small banks than large banks. Third, the documented relation between bank liquidity risk and liquidity holdings is less (more) pronounced for a bank headquartered in a high (low) social capital county. Fourth, the inverse relation between social capital and bank liquidity holdings is more (less) pronounced for low (high) risk taking banks. The effects are both economically and statistically significant. The findings are robust to alternative model specifications, different variable measurements and the test for endogeneity. Taken together, the evidence here indicates that social capital, as an environmental factor, can unlock inefficiently high levels of bank liquidity holdings.

This study provides insights into the understanding of how the social environment affects bank decisions and behaviour. The evidence in this paper suggests that social capital plays a role through its effects on trust, contract enforcement, information-sharing mechanisms, managerial opportunistic behaviour etc. Furthermore, the findings have important policy implications that are particularly relevant to Basel III. The results indicate that in addition to the closely monitoring of bank balance sheets to comply with new liquidity regulations, i.e., the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR), bank regulators should take the social capital in the county where the bank is headquartered into consideration as it also matters in bank liquidity holdings. While the results underpin the importance of social capital on bank liquidity, more research is needed to guide policy in this important area. I think it is a fruitful topic for future research.

Appendix 4.1 Constructing the social capital measure

This Appendix lists the variables used for constructing the social capital index at the county level, which are provided by the Northeast Regional Center for Rural Development (NRCRD) at the Pennsylvania State University. The NRCRD reports the variables and their data in three different data sets. The old data set, OLD_NRCRD, reports data for 1990, 1997 and 2005. The new data set, NEW_NRCRD1, reports data for 1997, 2005 and 2009. The new data set, NEW_NRCRD2, reports data for 2014. I use NEW_NRCRD1 data for 1997, 2005 and 2009. I linearly interpolate and fill the social capital data for the in-between years from 1998 to 2004 and 2006 to 2008, and then linearly extrapolate values for years 2010 to 2014. The reasons that I use NEW_NRCRD1 are as follows. First, OLD_NRCRD data might be incomplete (Hasan, Hoi, Wu and Zhang, 2017a; 2017b). Second, I observe significant discrepancies in the reported ASSN values between NEW_NRCRD1 and NEW_NRCRD2. Specifically, ASSN in NEW_NRCRD1 is calculated as the sum of social organizations divided by population per 100,000 in 1997, 2005 and 2009, while it is measured in NEW_NRCRD2 as the sum of social organizations divided by population per 1,000 in 2014. Following Rupasingha, Goetz and Freshwater (2006), *sc* is the first principal component from a principal component analysis based on PVOTE, RESPN, NCCS and ASSN. The following table lists the variables and definition.

Variable	Definition
Principal factors:	
PVOTE	Percentage of voters who voted in presidential elections
RESPN	Response rate to the Census Bureau's decennial census
NCCS	Number of tax-exempt non-profit organizations without including those with an international approach divided by population per 10,000
ASSN	Sum of social organizations divided by population per 100,000
Social organizations:	
RELIG	Number of religious organizations
CIVIC	Number of civic and social associations
BUS	Number of business associations
POL	Number of political organizations
PROF	Number of professional organizations
LABOR	Number of labor organizations
BOWL	Number of bowling centers
FITNS	Number of physical fitness facilities
GOLF	Number of public golf courses
SPORT	Number of sports clubs, managers, and promoters

Source: Northeast Regional Center for Rural Development (NRCRD)

Appendix 4.2 Variable definitions

Variable	Definition
Panel A: Bank liquidity, social capital and bank failure risk variables	
liqhod	The sum of all cash and balances due from other financial institutions, fed funds sold less fed funds bought, and securities purchased under resale agreements less securities sold under repurchase agreements, scaled by total assets.
sc	The social capital of the county where the bank is headquartered constructed as in Rupasingha, Goetz and Freshwater (2006)
Panel B: Bank-specific variables	
ca	Total equity capital to total risk-weighted assets
aq	Non-performing assets to total assets
mc	Cost-to-income ratio
earn	Ratio of net income to total assets
catfat_gta	Berger and Bouwman's (2009) preferred liquidity creation measure normalized by Gross Total Assets (GTA)
ltdrt	Loans-to-deposits ratio
ucrt	Ratio of unused loan commitments to total loans
noniirt	Ratio of non-interest income to total income
banksize	Natural logarithm of total assets
bhc	A dummy variable that takes one if bank holding company (BHC) status applies and zero if otherwise
Panel C: Macroeconomic and demographic variables	
sloos	Net percentage of domestic banks reporting stronger demand for commercial and industrial loans
spread	The difference between ten year Treasury yield and three month Treasury yield
lnperinc	Natural logarithm of per capita personal income in a county
lnemploy	Natural logarithm of total employment in a county
crisisdummy	An indicator variable equal to one if the observation occurs during 2007-2009 and zero otherwise

CHAPTER 5

CONCLUSION

5.1 Introduction

This thesis empirically investigates three key research questions related to bank liquidity, which have not been addressed in previous research and have imperative relevance to proficient bank management and policy making decisions. These questions are addressed in each of the self-contained chapters of this thesis. Chapter two investigates the liquidity-risk sharing function of bank capital in moderating the relationship between bank liquidity creation and failure risk. Chapter three examines the effects of government capital support in the context of TARP capital infusion on bank liquidity holdings and liquidity creation. Chapter four highlights the important role played by social capital in determining bank liquidity holdings.

5.2 Summary of major findings

The ***second chapter*** sheds new light on the association between bank liquidity creation and bank failure risk. The key insight in this chapter is the liquidity-risk sharing function of bank capital in moderating the relationship between bank liquidity creation and failure risk. The findings of this chapter suggest that without controlling for bank capital, liquidity creation is positively associated with bank failure risk. However, once controlling for bank capital, liquidity creation is significantly negative associated with bank failure risk. I also find that the significantly negative relationship between bank liquidity creation and bank failure risk is more prominent for small banks and the impact of bank capital was more pronounced during the recent financial crisis period.

This chapter makes important contributions to the literature. Firstly, to date, little research has empirically analysed the role played by bank capital in moderating the relationship between bank liquidity creation and bank failures. This study sheds new light on this liquidity risk-sharing function of bank capital because it is important to consider the endogenous reaction of banks (e.g., banks may actively adjust their capital ratio) towards higher liquidity risk stemming from liquidity creation. Secondly, this study has important policy implications for policymakers and bank regulators as it provides novel insights for the design of prudential regulation and supervision of banks. Prudential regulation, in the form of liquidity or capital requirements, is designed to enhance the resilience of the banking system to shocks by requiring institutions to maintain prudent levels of liquidity and capital under a broad range of market conditions. The results in this paper suggest that capital and liquidity requirements cannot be isolated. Further, the results clearly show that one size does not fit all when it comes to capital and liquidity regulation. Presumably, large banks might underestimate liquidity risk and maintain low capital ratios because of their too-big-to-fail position. The findings indicate that stringent capital requirements should be imposed on large banks to induce them to raise capital and reduce the probability of failure.

The ***third chapter*** in this thesis focuses on the effects of government bailout on bank liquidity holdings and liquidity creation. TARP, the largest government rescue program in the U.S. history, provides a natural testing ground to identify the relationship between government capital support and bank liquidity. The incentives of banks to hoard liquid assets are driven by two reasons: precautionary motive and strategic motive (Gale and Yorulmazer, 2013). However, a bank's precautionary and strategic demand for liquidity may be excessive and not optimal. This would in turn suggest possible policy interventions to address excessive hoarding of liquidity by banks. The findings of this study provide strong evidence that higher government capital support (TARP) is associated with lower levels of liquidity holdings, consistent with the precautionary and strategic motives of liquidity holdings in the banking literature. Finally, further analysis reveals that the TARP program not only unlocked liquidity holdings but also achieved the stated purpose of increasing bank lending/liquidity creation.

This chapter contributes significantly to the government bailout literature. The primary contribution of this paper to the existing literature is that it provides additional evaluation of the effectiveness of the TARP program, and will be of particular importance to policymakers for assessing and designing government-supported schemes. This study has important policy implications as it suggests that government capital support (e.g., TARP recapitalization) assists economic recovery by reducing liquidity hoarding behaviour of banks, and stimulating bank lending and/or liquidity creation. All these positive implications of TARP are of primary concern for governments and policy authorities, particularly in an era of on-going economic and financial turbulence in the aftermath of the recent global financial meltdown. This paper expands upon the bank lending channel literature by broadening the focus to bank liquidity creation – which includes much more than lending, as bank lending is only one component of asset-side liquidity creation. It is important to study liquidity creation because, according to the modern theory of financial intermediation, liquidity creation is a core function of banks to support the macro-economy. Perhaps more importantly, liquidity creation is viewed as the best available measure of total bank output.

The ***fourth chapter*** examines whether social capital at the county level in the U.S., as captured by the strength of civic norms and the density of social networks in a county, affects the liquidity holdings of banks headquartered in that county. The findings of this chapter show that banks with headquarters located in counties with higher levels of social capital show lower precautionary demand for liquidity holdings. The effect of social capital on liquidity holdings is also stronger for small banks than large banks. Moreover, this study finds that the positive relation between bank liquidity risk and liquidity holdings is less (more) pronounced for banks headquartered in the high (low) social capital counties, and the inverse relation between social capital and bank liquidity holdings is more (less) pronounced for low (high) risk taking banks. These results suggest that social capital plays an important role in reducing inefficiently high levels of liquidity holdings by banks.

The contribution of the paper is threefold. Firstly, this study contributes to a more comprehensive understanding of the determinants of bank liquidity holdings.

While prior research has investigated the role played by financial factors (e.g., CAMELS rating) in determining bank liquidity holdings, little attention has been paid to the role played by non-financial factors (e.g., social capital). This study provides an analysis of a previously unexplored factor – the effect of social capital on the efficiency of bank liquidity levels. Secondly, the findings of this paper have important implications for banking regulation under Basel III initiatives. It is documented that liquidity risk led to the hoarding of liquid assets and widespread bank failures during the global financial crisis (Radde, 2015; DeYoung and Jang, 2016). In response to this, the Basel Committee on Banking Supervision has proposed the Basel III Accord in 2010. It requires banks to alter their balance sheets to comply with two new liquidity regulations: the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR). Hence, liquidity risk management has become one of the top priorities for regulators. It is well known that regulators impose and adjust liquidity requirements of banks for safety and soundness reasons. The evidence in this study indicates that bank supervisors and regulators should not only actively monitor the balance sheets of banks, but also pay special attention to the social capital in the counties where banks are headquartered since social capital affects bank liquidity holdings. This supports the application of other criteria to complement the traditional, micro-prudential banking regulation approach. Thirdly, this study contributes to the emerging literature on the effects of social capital on corporate decision-making and behaviour (Javakhadze, Ferris and French, 2016a; Hasan, Hoi, Wu and Zhang, 2017a). In this regard, the results of this research indicate that social capital may provide banks with assurance of safety, which in turn reduces inefficiently high levels of precautionary liquidity holdings by banks. The findings also serve as indication that the social environment, in the context of norms and networks surrounding bank headquarters, limit the opportunistic behaviour (e.g., excessive risk taking) of bank management, which in turn alleviates banks' precautionary motives for holding liquidity. Further, the paper is closely related to recent literature on professional and personal connections and networks (e.g., Ferris, Javakhadze and Rajkovic, 2017). This study complements these papers by providing evidence that the local social environment, such as social capital and trust, rather than professional and personal connections, have an important effect on bank management and policy.

5.3 Directions for future research

The findings of this thesis add to the understanding of bank liquidity holdings and liquidity creation from different perspectives, but the findings also underpin other research questions that are to be answered in the future to enhance bank policies.

Firstly, more research is needed as to whether the Basel III liquidity requirement – liquidity coverage ratio (LCR) and the net stable funding ratio (NSFR), affects the relationship between bank liquidity creation and failure risk. For robustness check, one may investigate whether and how a bank's liquidity management policy affects the link between bank capital, liquidity creation and the probability of default. Secondly, although the findings of this thesis suggest that government capital support can unlock high levels of inefficient liquid asset holdings by banks, there is a potential venue for future research to explore how other government assistance programs, such as blanket guarantees, liquidity provisions, government-assisted mergers etc. affect bank liquidity holdings. Thirdly, while this thesis underpins the importance of social capital as a determinant of bank liquidity holdings, more research is needed to incorporate other non-financial and/or non-macroeconomic factors that may implicate the liquidity management of banks. Last but not least, the three distinct but interrelated topics in this thesis are based on U.S. data. Admittedly, the conclusions from these studies cannot be generalized because of the focus on a single country. Therefore, similar international empirical research will contribute. These interesting issues are beyond the scope of this article, but may be pursued in future research.

References

Acharya, V. V., Drechsler, I., & Schnabl, P. (2014). A pyrrhic victory? Bank bailouts and sovereign credit risk. *The Journal of Finance, 69*(6), 2689-2739.

Acharya, V. V., & Naqvi, H. (2012). The seeds of a crisis: A theory of bank liquidity and risk taking over the business cycle. *Journal of Financial Economics, 106*(2), 349-366.

Acharya, V. V., Gromb, D., & Yorulmazer, T. (2012). Imperfect Competition in the Interbank Market for Liquidity as a Rationale for Central Banking. *American Economic Journal: Macroeconomics, 4*(2), 184-217.

Acharya, V. V., Mehran, H., & Thakor, A. V. (2016). Caught between Scylla and Charybdis? Regulating Bank Leverage When There Is Rent Seeking and Risk Shifting. *The Review of Corporate Finance Studies, 5*(1), 36-75.

Acharya, V. V., & Merrouche, O. (2012). Precautionary Hoarding of Liquidity and Interbank Markets: Evidence from the Subprime Crisis. *Review of Finance*.

Acharya, V. V., & Mora, N. (2015). A Crisis of Banks as Liquidity Providers. *The Journal of Finance, 70*(1), 1-43.

Acharya, V. V., Shin, H. S., & Yorulmazer, T. (2011). Crisis Resolution and Bank Liquidity. *Review of Financial Studies, 24*(6), 2166.

Acharya, V. V., & Skeie, D. (2011). A model of liquidity hoarding and term premia in inter-bank markets. *Journal of Monetary Economics, 58*(5), 436-447.

Acharya, V. V., & Yorulmazer, T. (2007). Too many to fail—An analysis of time-inconsistency in bank closure policies. *Journal of Financial Intermediation, 16*(1), 1-31.

Afonso, G., Kovner, A., & Schoar, A. (2011). Stressed, Not Frozen: The Federal Funds Market in the Financial Crisis. *The Journal of Finance, 66*(4), 1109-1139.

Allen, F., Carletti, E., & Gale, D. (2009). Interbank market liquidity and central bank intervention. *Journal of Monetary Economics, 56*(5), 639-652.

Allen, F., & Gale, D. (2004). Financial Intermediaries and Markets. *Econometrica, 72*(4), 1023-1061.

Allen, F., & Santomero, A. M. (1997). The theory of financial intermediation. *Journal of Banking & Finance, 21*(11), 1461-1485.

Allen, L., Peristiani, S., & Saunders, A. (1989). Bank size, collateral, and net purchase behavior in the federal funds market: Empirical evidence. *Journal of Business*, 501-515.

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

Armendáriz de Aghion, B. (1999). On the design of a credit agreement with peer monitoring. *Journal of Development Economics, 60*(1), 79-104.

Ashcraft, A., McAndrews, J., & Skeie, D. (2011). Precautionary Reserves and the Interbank Market. *Journal of Money, Credit, and Banking, 43*, 311.

Aubuchon, C. P., & Wheelock, D. C. (2010). The Geographic Distribution and Characteristics of U.S. Bank Failures, 2007-2010: Do Bank Failures Still Reflect Local Economic Conditions? Federal Reserve Bank of St. Louis Review *(00149187), 92*(5), 395-415.

Baltas, K. N., Kapetanios, G., Tsionas, E., & Izzeldin, M. (2017). Liquidity creation through efficient M&As: A viable solution for vulnerable banking systems?

Evidence from a stress test under a panel VAR methodology. *Journal of Banking & Finance, 83*, 36-56.

Banerjee, A. V., Besley, T., & Guinnane, T. W. (1994). Thy neighbor's keeper: The design of a credit cooperative with thoery and a test. *Quarterly Journal of Economics*, *109*(2), 491-515.

Bayazitova, D., & Shivdasani, A. (2012). Assessing TARP. *Review of Financial Studies, 25*(2), 377-407.

Berger, A. N., Bouwman, C. H. S., & Kim, D. (2017). Small bank comparative advantages in alleviating financial constraints and providing liquidity insurance over time. *The Review of Financial Studies,* hhx038.

Berger, A. N., & Bouwman, C. H. S. (2009). Bank Liquidity Creation. *The Review of Financial Studies, 22*(9), 3779-3837.

Berger, A. N., & Bouwman, C. H. S. (2013). How does capital affect bank performance during financial crises? *Journal of Financial Economics, 109*(1), 146-176.

Berger, A. N., & Bouwman, C. H. S. (2017). Bank liquidity creation, monetary policy, and financial crises. *Journal of Financial Stability, 30*, 139-155.

Berger, A. N., Bouwman, C. H. S., Kick, T., & Schaeck, K. (2016). Bank liquidity creation following regulatory interventions and capital support. *Journal of Financial Intermediation, 26*, 115-141.

Berger, A. N., Imbierowicz, B., & Rauch, C. (2016). The Roles of Corporate Governance in Bank Failures during the Recent Financial Crisis. *Journal of Money, Credit and Banking, 48*(4), 729-770.

Berger, A. N., & Roman, R. A. (2015). Did TARP banks get competitive advantages? *Journal of Financial and Quantitative Analysis*, *50*(06), 1199-1236.

Berger, A. N., & 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,* 1-41.

Berger, A. N., & Sedunov, J. (2017). Bank liquidity creation and real economic output. *Journal of Banking & Finance, 81*, 1-19.

Berrospide, J. (2013). Bank liquidity hoarding and the financial crisis: an empirical evaluation (November 29, 2012). FEDS Working Paper No. 2013-03. Available at SSRN: *https://ssrn.com/abstract=2207754*

Besley, T., & Coate, S. (1995). Group lending, repayment incentives and social collateral. *Journal of Development Economics, 46*(1), 1-18.

Bhagat, S., Bolton, B., & Lu, J. (2015). Size, leverage, and risk-taking of financial institutions. *Journal of Banking & Finance, 59*, 520-537.

Bhattacharya, S., & Gale, D. (1987). Preference Shocks, Liquidity and Central Bank Policy. New approaches to monetary economics, Edited by William Barnett and Kenneth Singleton: Cambridge University Press.

Bhattacharya, S., & Thakor, A. V. (1993). Contemporary Banking Theory. *Journal of Financial Intermediation, 3*(1), 2-50.

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

Blau, B. M., Brough, T., & Thomas, D. (2013). Corporate lobbying, political connections, and the bailout of banks. *Journal of Banking & Finance, 37*(8), 3007-3017.

Bouwman, C. H. (2013). Liquidity: How banks create it and how it should be regulated (October 25, 2013). The Oxford Handbook of Banking, 2nd edition, A.N.

Berger, P. Molyneux, and J.O.S. Wilson, eds, Forthcoming. Available at SSRN: *https://ssrn.com/abstract=2307727*

Brunnermeier, M. K., & Pedersen, L. H. (2005). Predatory Trading. *The Journal of Finance, 60*(4), 1825-1863.

Bryant, J. (1980). A model of reserves, bank runs, and deposit insurance. *Journal of Banking & Finance, 4*(4), 335-344.

Buonanno, P., Montolio, D., & Vanin, P. (2009). Does Social Capital Reduce Crime? *The Journal of Law & Economics, 52*(1), 145-170.

Cadman, B., Carter, M. E., & Lynch, L. J. (2012). Executive Compensation Restrictions: Do They Restrict Firms' Willingness to Participate in TARP? *Journal of Business Finance & Accounting, 39*(7/8), 997-1027.

Cai, J., Walkling, R. A., & Yang, K. (2016). The Price of Street Friends: Social Networks, Informed Trading, and Shareholder Costs. *Journal of Financial & Quantitative Analysis, 51*(3), 801-837.

Cai, Y., & Sevilir, M. (2012). Board connections and M&A transactions. *Journal of Financial Economics, 103*(2), 327-349.

Calderon, C., & Schaeck, K. (2012). Bank bailouts, competitive distortions, and consumer welfare. *Bano Central do Brasil.* Available at *http://www. bc. gov. br/pec/depep/Seminarios/2012_VIISemRiscosBCB/Arquivos/2012_VIISemRiscosBCB_Ceasar _Calderon. pdf.*

Calomiris, C.W., & Khan, U. (2015). An assessment of TARP assistance to financial institutions. *Journal of Economic Perspectives, 29*(2), 53-80.

Campello, M. (2002). Internal Capital Markets in Financial Conglomerates: Evidence from Small Bank Responses to Monetary Policy. *The Journal of Finance, 57*(6), 2773-2805.

Cassar, A., Crowley, L., & Wydick, B. (2007). The effect of social capital on group loan repayment: evidence from field experiments*. *The Economic Journal, 117*(517), F85-F106.

Castiglionesi, F., Feriozzi, F., LÓRÁNth, G., & Pelizzon, L. (2014). Liquidity Coinsurance and Bank Capital. *Journal of Money, Credit and Banking, 46*(2-3), 409-443.

Chang, S. H., Contessi, S., & Francis, J. L. (2014). Understanding the accumulation of bank and thrift reserves during the US financial crisis. *Journal of Economic Dynamics and Control, 43*, 78-106.

Chatterjee, U. K. (2015). Bank liquidity creation and asset market liquidity. *Journal of Financial Stability, 18*, 139-153.

Chen, X., Zhou, L., & Wan, D. (2016). Group social capital and lending outcomes in the financial credit market: An empirical study of online peer-to-peer lending. *Electronic Commerce Research and Applications, 15*, 1-13.

Christensen, J. H. E., Lopez, J. A., & Rudebusch, G. D. (2013). Do Central Bank Liquidity Facilities Affect Interbank Lending Rates? *Journal of Business & Economic Statistics, 32*(1), 136-151.

Cialdini, R. B., Kallgren, C. A., & Reno, R. R. (1991). A focus theory of normative conduct: A theoretical refinement and reevaluation of the role of norms in human behavior. *Advances in experimental social psychology, 24*, 201-234.

Cleary, S., & Hebb, G. (2016). An efficient and functional model for predicting bank distress: In and out of sample evidence. *Journal of Banking & Finance, 64*, 101-111.

Cole, R. A., & Gunther, J. W. (1995). Separating the likelihood and timing of bank failure. *Journal of Banking & Finance, 19*(6), 1073-1089.

Cole, R. A., & Gunther, J. W. (1998). Predicting Bank Failures: A Comparison of On- and Off-Site Monitoring Systems. *Journal of Financial Services Research, 13*(2), 103-117.

Cole, R. A., & White, L. J. (2012). Deja Vu All Over Again: The Causes of U.S. Commercial Bank Failures This Time Around. *Journal of Financial Services Research, 42*(1-2), 5-29.

Coleman, J. S. (1988). Social capital in the creation of human capital. *American Journal of Sociology, 94*(1988), S95-120.

Coleman, J. S. (1990). *Foundations of social theory / James S. Coleman*. Cambridge, Mass.: Belknap Press of Harvard University Press.

Contessi, S., & Francis, J. L. (2011). TARP beneficiaries and their lending patterns during the financial crisis. Federal Reserve Bank of St. Louis Review, *93*.

Cooney, J. W., Madureira, L., Singh, A. K., & Yang, K. (2015). Social ties and IPO outcomes. *Journal of Corporate Finance, 33*, 129-146.

Cornett, M. M., Li, L., & Tehranian, H. (2013). The performance of banks around the receipt and repayment of TARP funds: Over-achievers versus under-achievers. *Journal of Banking & Finance, 37*(3), 730-746.

Cornett, M. M., McNutt, J. J., Strahan, P. E., & Tehranian, H. (2011). Liquidity risk management and credit supply in the financial crisis. *Journal of Financial Economics, 101*(2), 297-312.

Coval, J. D., & Thakor, A. V. (2005). Financial intermediation as a beliefs-bridge between optimists and pessimists. *Journal of Financial Economics, 75*(3), 535-569.

Dam, L., & Koetter, M. (2012). Bank bailouts and moral hazard: Evidence from Germany. *Review of Financial Studies, 25*(8), 2343-2380.

de Haan, L., & van den End, J. W. (2013). Banks' responses to funding liquidity shocks: Lending adjustment, liquidity hoarding and fire sales. *Journal of International Financial Markets, Institutions & Money, 26*, 152.

De Jonghe, O. G., Diepstraten, M., & Schepens, G. (2015). Banks' size, scope and systemic risk: What role for conflicts of interest? *Journal of Banking & Finance, 61* (Supplement 1), S3-S13.

Dell'ariccia, G., Igan, D., & Laeven, L. (2012). Credit Booms and Lending Standards: Evidence from the Subprime Mortgage Market. *Journal of Money, Credit and Banking, 44*(2-3), 367-384.

DeYoung, R., Distinguin, I., & Tarazi, A. (2018). The joint regulation of bank liquidity and bank capital, *Journal of Financial Intermediation*, forthcoming.

DeYoung, R., & Jang, K. Y. (2016). Do banks actively manage their liquidity? *Journal of Banking & Finance, 66*, 143-161.

DeYoung, R., & Torna, G. (2013). Nontraditional banking activities and bank failures during the financial crisis. *Journal of Financial Intermediation*.

Diamond, D. W., & Dybvig, P. H. (1983). Bank Runs, Deposit Insurance, and Liquidity. *The Journal of Political Economy, 91*(3), 401.

Diamond, D. W., & Rajan, R. G. (2000). A Theory of Bank Capital. *The Journal of Finance, 55*(6), 2431-2465.

Diamond, D. W., & Rajan, R. G. (2001). Liquidity Risk, Liquidity Creation, and Financial Fragility: A Theory of Banking. *Journal of Political Economy, 109*(2), 287.

Diamond, D. W., & Rajan, R. G. (2011). Fear of Fire Sales, Illiquidity Seeking, and Credit Freezes. *The Quarterly Journal of Economics, 126*(2), 557.

Díaz, V., & Huang, Y. (2017). The role of governance on bank liquidity creation. *Journal of Banking & Finance, 77*, 137-156.

Distinguin, I., Roulet, C., & Tarazi, A. (2013). Bank regulatory capital and liquidity: Evidence from US and European publicly traded banks. *Journal of Banking & Finance, 37*(9), 3295-3317.

Dong, W., Han, H., Ke, Y., & Chan, K. C. (2016). Social Trust and Corporate Misconduct: Evidence from China. *Journal of Business Ethics*, 1-24.

Duchin, R., & Sosyura, D. (2012). The politics of government investment. *Journal of Financial Economics, 106*(1), 24-48.

Duchin, R., & Sosyura, D. (2014). Safer ratios, riskier portfolios: Banks′ response to government aid. *Journal of Financial Economics, 113*(1), 1-28.

Duchin, R., & Sosyura, D. (2013). Divisional Managers and Internal Capital Markets. *The Journal of Finance, 68*(2), 387-429.

Elyasiani, E., Mester, L. J., & Pagano, M. S. (2014). Large capital infusions, investor reactions, and the return and risk-performance of financial institutions over the business cycle. *Journal of Financial Stability, 11*, 62-81.

Engelberg, J., Gao, P., & Parsons, C. A. (2012). Friends with money. *Journal of Financial Economics, 103*(1), 169-188.

Engelberg, J., Gao, P., & Parsons, C. A. (2013). The Price of a CEO's Rolodex. *Review of Financial Studies, 26*(1), 79-114.

Erickson, T., Jiang, C. H., & Whited, T. M. (2014). Minimum distance estimation of the errors-in-variables model using linear cumulant equations. *Journal of Econometrics, 183*(2), 211-221.

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

Fazzari, S. M., & Petersen, B. C. (1993). Working capital and fixed investment: new evidence on financing constraints. *The RAND Journal of Economics*, 328-342.

Ferrary, M. (2003). Trust and social capital in the regulation of lending activities. *Journal of Socio-Economics, 31*(6), 673-699.

Ferreira, M. A., & Matos, P. (2012). Universal Banks and Corporate Control: Evidence from the Global Syndicated Loan Market. *Review of Financial Studies, 25*(9), 2703-2744.

Ferris, S. P., Javakhadze, D., & Rajkovic, T. (2017). The international effect of managerial social capital on the cost of equity. *Journal of Banking & Finance, 74*, 69-84.

Fidrmuc, J., Fungáčová, Z., & Weill, L. (2015). Does Bank Liquidity Creation Contribute to Economic Growth? Evidence from Russia. *Open Economies Review, 26*(3), 479-496.

Fischer, M., Hainz, C., Rocholl, J., & Steffen, S. (2014). Government guarantees and bank risk taking incentives (March 16, 2014). CESifo Working Paper Series No. 4706. Available at SSRN: *https://ssrn.com/abstract=2425525*

Flannery, M. J. (2010). What to do about TBTF? Unpublished working paper. University of Florida.

Fleming, M. J. (2012). Federal Reserve liquidity provision during the financial crisis of 2007-2009. *Federal Reserve Bank of New York Staff Report*(563).

Fu, X., Lin, Y., & Molyneux, P. (2016). BANK CAPITAL AND LIQUIDITY CREATION IN ASIA PACIFIC. *Economic Inquiry, 54*(2), 966-993.

Fungáčová, Z., Turk, R., & Weill, L. (2015). *High Liquidity Creation and Bank Failures*. IMF Working Paper. Washington: International Monetary Fund

Fungáčová, Z., Weill, L., & Zhou, M. (2017). Bank Capital, Liquidity Creation and Deposit Insurance. *Journal of Financial Services Research, 51*(1), 97-123.

Gale, D., & Yorulmazer, T. (2013). Liquidity hoarding. *Theoretical Economics, 8*(2), 291-324.

Gârleanu, N., & Pedersen, L. H. (2007). Liquidity and Risk Management. *American Economic Review, 97*(2), 193-197.

Gatev, E., Schuermann, T., & Strahan, P. E. (2009). Managing Bank Liquidity Risk: How Deposit-Loan Synergies Vary with Market Conditions. *Review of Financial Studies, 22*(3), 995-1020.

Gatev, E., & Strahan, P. E. (2006). Banks' Advantage in Hedging Liquidity Risk: Theory and Evidence from the Commercial Paper Market. *The Journal of Finance, 61*(2), 867-892.

Ghatak, M. (1999). Group lending, local information and peer selection. *Journal of Development Economics, 60*(1), 27-50.

Giannetti, M., & Simonov, A. (2013). On the real effects of bank bailouts: micro evidence from Japan. *American Economic Journal: Macroeconomics, 5*(1), 135-167.

Goldsmith-Pinkham, P., & Yorulmazer, T. (2010). Liquidity, Bank Runs, and Bailouts: Spillover Effects During the Northern Rock Episode. *Journal of Financial Services Research, 37*(2/3), 83-98.

Goodhart, C. A., & Huang, H. (2005). The lender of last resort. *Journal of Banking & Finance, 29*(5), 1059-1082.

Gorton, G., & Huang, L. (2002). Banking panics and the origin of central banking: National Bureau of Economic Research.

Gorton, G., & Winton, A. (2017). Liquidity Provision, Bank Capital, and the Macroeconomy. *Journal of Money, Credit and Banking, 49*(1), 5-37.

Greiner, M. E., & Wang, H. (2009). The role of social capital in people-to-people lending marketplaces. *ICIS 2009 proceedings*, Paper 29, 2009.

Gropp, R., Hakenes, H., & Schnabel, I. (2011). Competition, risk-shifting, and public bail-out policies. *Review of Financial Studies, 24*(6), 2084-2120.

Guiso, L., Sapienza, P., & Zingales, L. (2004). The Role of Social Capital in Financial Development. *American Economic Review, 94*(3), 526-556.

Hambrick, D. C. (2007). Upper Echelons Theory: An Update. *The Academy of Management Review, 32*(2), 334-343.

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

Hasan, I., Hoi, C. K., Wu, Q., & Zhang, H. (2017a). Does Social Capital Matter in Corporate Decisions? Evidence from Corporate Tax Avoidance. *Journal of Accounting Research, 55*(3), 629-668.

Hasan, I., Hoi, C. K., Wu, Q., & Zhang, H. (2017b). Social Capital and Debt Contracting: Evidence from Bank Loans and Public Bonds. *Journal of Financial and Quantitative Analysis, 52*(3), 1017-1047.

Hausman, J. A. (1978). Specification Tests in Econometrics. *Econometrica, 46*(6), 1251-1271.

Heckman, J. J. (1979). Sample Selection Bias as a Specification Error. *Econometrica, 47*(1), 153-161.

Heider, F., Hoerova, M., & Holthausen, C. (2015). Liquidity hoarding and interbank market rates: The role of counterparty risk. *Journal of Financial Economics, 118*(2), 336-354.

Hesse, H., & Frank, N. (2009). The effectiveness of central bank interventions during the first phase of the subprime crisis: *IMF Working Papers* No. 09/206.

Hesse, H., Frank, N., & González-Hermosillo, B. (2008). Transmission of liquidity shocks: Evidence from the 2007 subprime crisis. *IMF Working Papers,* 1-21.

Hilary, G., & Hui, K. W. (2009). Does religion matter in corporate decision making in America? *Journal of Financial Economics, 93*(3), 455-473.

Holmström, B., & Tirole, J. (1998). Private and public supply of liquidity. *Journal of Political Economy, 106*(1), 1.

Hong, H., Huang, J. Z., & Wu, D. (2014). The information content of Basel III liquidity risk measures. *Journal of Financial Stability, 15*, 91-111.

Horváth, R., Seidler, J., & Weill, L. (2016). How bank competition influences liquidity creation. *Economic Modelling, 52*, 155-161.

Horváth, R., Seidler, J., & Weill, L. (2014). Bank Capital and Liquidity Creation: Granger-Causality Evidence. *Journal of Financial Services Research, 45*(3), 341-361.

Hoshi, T., & Kashyap, A. K. (2010). Will the US bank recapitalization succeed? Eight lessons from Japan. *Journal of Financial Economics, 97*(3), 398-417.

Houston, J. F., & James, C. (1998). Do bank internal capital markets promote lending? *Journal of Banking & Finance, 22*(6–8), 899-918.

Hryckiewicz, A. (2012). Government Interventions-Restoring or Destroying Financial Stability in the Long-Run? Wharton Financial Institutions Center Working Paper 12-02. Available at SSRN: *https://ssrn.com/abstract=1978776*

Huang, Q., Jiang, F., Lie, E., & Yang, K. (2014). The role of investment banker directors in M&A. *Journal of Financial Economics, 112*(2), 269-286.

Huerta, D., Perez-Liston, D., & Jackson, D. (2011). The impact of TARP bailouts on stock market volatility and investor fear. *Banking and Finance Review, 3*(1), 45-54.

Imbierowicz, B., & Rauch, C. (2014). The relationship between liquidity risk and credit risk in banks. *Journal of Banking & Finance, 40*, 242-256.

Javakhadze, D., Ferris, S., & French, D. (2016a). Social capital, investments, and external financing. *Journal of Corporate Finance, 37*, 38.

Javakhadze, D., Ferris, S., & French, D. (2016b). Managerial Social Capital and Financial Development: A Cross-Country Analysis. *Financial Review, 51*(1), 37-68.

Jha, A., & Chen, Y. (2015). Audit fees and social capital. *Accounting Review, 90*(2), 611-639.

Jha, A., & Cox, J. (2015). Corporate social responsibility and social capital. *Journal of Banking & Finance, 60*, 252-270.

Jiang, L., Levine, R., & Lin, C. (2016). Competition and bank liquidity creation: National Bureau of Economic Research.

Jin, J. Y., Kanagaretnam, K., & Lobo, G. J. (2011). Ability of accounting and audit quality variables to predict bank failure during the financial crisis. *Journal of Banking & Finance, 35*(11), 2811-2819.

Jin, J. Y., Kanagaretnam, K., Lobo, G. J., & Mathieu, R. (2017). Social capital and bank stability. *Journal of Financial Stability, 32*(Supplement C), 99-114.

Jordan, D. J., Rice, D., Sanchez, J., & Wort, D. H. (2011). Explaining bank market-to-book ratios: Evidence from 2006 to 2009. *Journal of Banking & Finance, 35*(8), 2047-2055.

Kandori, M. (1992). Social Norms and Community Enforcement. *The Review of Economic Studies, 59*(1), 63-80.

Karlan, D. S. (2007). Social connections and group banking*. *The Economic Journal, 117*(517), F52-F84.

Kashyap, A. K., Rajan, R., & Stein, J. C. (2002). Banks as Liquidity Providers: An Explanation for the Coexistence of Lending and Deposit-Taking. *The Journal of Finance, 57*(1), 33-73.

Kashyap, A. K., & Stein, J. C. (2000). What Do a Million Observations on Banks Say About the Transmission of Monetary Policy? *American Economic Review, 90*(3), 407-428.

Khan, M. S., Scheule, H., & Wu, E. (2017). Funding liquidity and bank risk taking. *Journal of Banking and Finance, 82*, 203-216.

Kim, C. S., Mauer, D. C., & Sherman, A. E. (1998). The Determinants of Corporate Liquidity: Theory and Evidence. *Journal of Financial and Quantitative Analysis, 33*(3), 335-359.

Kim, D. H., & Stock, D. (2012). Impact of the TARP financing choice on existing preferred stock. *Journal of Corporate Finance, 18*(5), 1121-1142.

Kim, W. Y. (2010). Market reaction to limiting executive compensation: evidence from TARP firms (March 29,2010). Available at SSRN: *https://ssrn.com/abstract=1553394*

Knack, S., & Keefer, P. (1997). Does social capital have an economic payoff? A cross-country investigation. *The Quarterly Journal of Economics, 112*(4), 1251-1288.

Koetter, M., & Noth, F. (2012). Competitive distortions of bank bailouts: Working Paper, Frankfurt School of Finance and Management.

La Porta, R., Shleifer, A., & Vishny, R. W. (1997). Trust in Large Organizations. *The American Economic Review, 87*(2), 333-338.

Laeven, L., Ratnovski, L., & Tong, H. (2016). Bank size, capital, and systemic risk: Some international evidence. *Journal of Banking & Finance, 69*, S25-S34.

Laeven, L., & Valencia, F. (2012). The use of blanket guarantees in banking crises. *Journal of International Money and Finance, 31*(5), 1220-1248.

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

Li, P., Tang, L., & Jaggi, B. (2016). Social Capital and the Municipal Bond Market. *Journal of Business Ethics*, 1-23.

Lin, M., Prabhala, N. R., & Viswanathan, S. (2013). Judging Borrowers by the Company They Keep: Friendship Networks and Information Asymmetry in Online Peer-to-Peer Lending. *Management Science, 59*(1), 17-35.

Liu, Q., Luo, J., & Tian, G. (2016). Managerial professional connections versus political connections: Evidence from firms' access to informal financing resources. *Journal of Corporate Finance, 41*, 179-200.

Liu, W., Kolari, J. W., Kyle Tippens, T., & Fraser, D. R. (2013). Did capital infusions enhance bank recovery from the great recession? *Journal of Banking & Finance, 37*(12), 5048-5061.

Mailath, G. J., & Mester, L. J. (1994). A positive analysis of bank closure. *Journal of Financial Intermediation, 3*(3), 272-299.

McAndrews, J., Sarkar, A., & Wang, Z. (2008). The effect of the term auction facility on the London inter-bank offered rate. *Federal Reserve Bank of New York Staff Report*(335).

McMillan, J., & Woodruff, C. (2000). Private order under dysfunctional public order. *Michigan Law Review, 98*(8), 2421-2459.

Michaud, F. L., & Upper, C. (2008). What drives interbank rates? Evidence from the Libor panel. *BIS Quarterly Review, March*.

Mutu, S., & Corovei, E. (2013). Liquidity hoarding behavior during the financial crisis. Empirical evidence from the European banking system. Working Paper at Babes-Bolyai University of Cluj-Napoca.

Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, *13*(2), 187-221.

Myers, S. C., & Rajan, R. G. (1998). The Paradox of Liquidity. *The Quarterly Journal of Economics, 113*(3), 733-771.

Ng, J., & Roychowdhury, S. (2014). Do loan loss reserves behave like capital? Evidence from recent bank failures. *Review of Accounting Studies*, *19*(3), 1234-1279.

Ng, J., Vasvari, F. P., & Wittenberg-Moerman, R. (2016). Media Coverage and the Stock Market Valuation of TARP Participating Banks. *European Accounting Review*, 25 (2016), 347-371.

Nguyen, A. P., & Enomoto, C. E. (2009). The Troubled Asset Relief Program (TARP) and the financial crisis of 2007-2008. *Journal of Business & Economics Research*, *7*(12), 91.

Norden, L., Roosenboom, P., & Wang, T. (2011). The impact of government intervention in banks on corporate borrowers' stock returns. *Rotterdam School of Management manuscript, Erasmus University*.

Norton, E. C., Wang, H., & Ai, C. (2004). Computing interaction effects and standard errors in logit and probit models. *Stata Journal*, *4*(2), 154-167.

Opler, T., Pinkowitz, L., Stulz, R., & Williamson, R. (1999). The determinants and implications of corporate cash holdings. *Journal of Financial Economics, 52*(1), 3-46.

Ostergaard, C., Schindele, I., & Vale, B. (2016). Social Capital and the Viability of Stakeholder-Oriented Firms: Evidence from Savings Banks. *Review of Finance*, *20*(5), 1673-1718.

Pana, E., Park, J., & Query, T. (2010). The impact of bank mergers on liquidity creation. *Journal of Risk Management in Financial Institutions*, *4*(1), 74-96.

Peri, G. (2004). Socio-Cultural Variables and Economic Success: Evidence from Italian Provinces 1951-1991. *Topics in Macroeconomics*, *4*(1).

Philippon, T., & Schnabl, P. (2013). Efficient recapitalization. *The Journal of Finance, 68*(1), 1-42.

Puddu, S., & Waelchli, A. (2015). TARP Effect on Bank Lending Behaviour: Evidence from the last Financial Crisis. *IDEAS Working Paper Series from RePEc*.

Putnam, R. D. (1993). *Making democracy work : civic traditions in modern Italy / Robert D. Putnam with Robert Leonardi and Raffaella Y. Nanetti*. Princeton, N.J. : Princeton University Press.

Radde, S. (2015). Flight to liquidity and the Great Recession. *Journal of Banking & Finance, 54*, 192-207.

Repullo, R. (2004). Capital requirements, market power, and risk-taking in banking. *Journal of Financial Intermediation, 13*(2), 156-182.

Repullo, R. (2005). Liquidity, Risk Taking, and the Lender of Last Resort. *IDEAS Working Paper Series from RePEc*.

Rupasingha, A., & Goetz, S. J. (2007). Social and political forces as determinants of poverty: A spatial analysis. *Journal of Socio-Economics, 36*(4), 650-671.

Rupasingha, A., Goetz, S. J., & Freshwater, D. (2000). Social Capital and Economic Growth: A County-level Analysis. *Journal of Agricultural and Applied Economics, 32*(03).

Rupasingha, A., Goetz, S. J., & Freshwater, D. (2006). The production of social capital in US counties. *Journal of Socio-Economics, 35*(1), 83-101.

Sengupta, R., & Tam, Y. M. (2008). The LIBOR-OIS spread as a summary indicator. *Economic Synopses, 2008*(2008-10-15).

Stein, J. C. (1997). Internal Capital Markets and the Competition for Corporate Resources. *Journal of Finance, 52*(1), 111-133.

Stiglitz, J. E. (1990). Peer Monitoring and Credit Markets. *The World Bank Economic Review, 4*(3), 351-366.

Taliaferro, R. (2009). How do banks use bailout money? Optimal capital structure, new equity, and the TARP (December 21, 2009). Available at SSRN: *https://ssrn.com/abstract=1481256*

TARP Agency Financial Report (2014). Available at: https://www.treasury.gov/initiatives/financial-stability/reports/Documents/FY2014%20OFS%20AFR%20FINAL%20-%20Nov%206%202014.pdf

Thakor, A. V. (2005). Do Loan Commitments Cause Overlending? *Journal of Money, Credit, and Banking, 37*(6), 1067-1099.

Thornton, D. L. (2009). What the Libor-OIS spread says. *Economic Synopses, 2009*(2009-05-11).

Tran, V. T., Lin, C.T., & Nguyen, H. (2016). Liquidity creation, regulatory capital, and bank profitability. *International Review of Financial Analysis, 48*, 98-109.

Van Tassel, E. (1999). Group lending under asymmetric information. *Journal of Development Economics, 60*(1), 3-25.

Vazquez, F., & Federico, P. (2015). Bank funding structures and risk: Evidence from the global financial crisis. *Journal of Banking & Finance, 61*, 1-14.

Veronesi, P., & Zingales, L. (2010). Paulson's gift. *Journal of Financial Economics, 97*(3), 339-368.

Von Thadden, E. L. (2004). Bank capital adequacy regulation under the new Basel Accord. *Journal of Financial Intermediation, 13*(2), 90-95.

Wheelock, D. C., & Wilson, P. W. (2000). Why Do Banks Disappear? The Determinants of U.S. Bank Failures and Acquisitions. *Review of Economics & Statistics, 82*(1), 127.

Whited, T. M. (1992). Debt, Liquidity Constraints, and Corporate Investment: Evidence from Panel Data. *The Journal of Finance, 47*(4), 1425-1460.

Wilson, L. (2012). Debt overhang and bank bailouts. *International Journal of Monetary Economics and Finance, 5*(4), 395-414.

Wilson, L. (2013). TARP's deadbeat banks. *Review of Quantitative Finance and Accounting*, 1-24.

Wilson, L., & Wu, Y. W. (2010). Common (stock) sense about risk-shifting and bank bailouts. *Financial Markets and Portfolio Management, 24*(1), 3-29.

Wilson, L., & Wu, Y. W. (2012). Escaping TARP. *Journal of Financial Stability, 8*(1), 32-42.

Woolcock, M. (2001). The place of social capital in understanding social and economic outcomes. *Canadian journal of policy research, 2*(1), 11-17.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data* (2nd edition ed.): Cambridge, MA: MIT press.

Wu, W., Firth, M., & Rui, O. M. (2014). Trust and the provision of trade credit. *Journal of Banking & Finance*, *39*, 146-159.

Wu, W. P. (2008). Dimensions of Social Capital and Firm Competitiveness Improvement: The Mediating Role of Information Sharing. *Journal of Management Studies, 45*(1), 122-146.