Essays in corporate finance and banking

Author:
Choi, Seungho

Publication Date:
2019

DOI:
https://doi.org/10.26190/unsworks/3865

Essays in Corporate Finance and Banking

Seungho Choi

A thesis submitted to the University of New South Wales

in partial fulfilment of the requirements for the degree of

Doctor of Philosophy

School of Banking and Finance

University of New South Wales

August 2019

Thesis/Dissertation Sheet

Surname/Family Name	:	**CHOI**
Given Name/s	:	**SEUNGHO**
Abbreviation for degree as give in the University calendar	:	**PhD**
Faculty	:	**UNSW Business School**
School	:	**School of Banking and Finance**
Thesis Title	:	**Essays in Corporate Finance and Banking**

Abstract 350 words maximum: (PLEASE TYPE)

This thesis consists of three empirical studies about corporate finance and banking.

In the first chapter, I investigate how CEOs communicate with the market. CEOs have incentives to communicate with their investors after news releases if the market misinterprets the news. I examine how CEOs communicate with the market through their trading patterns. I find that CEOs are more likely to purchase shares after positive and negative news releases, suggesting that they want to confirm their positive news if the market underreacts to it and want to mitigate the market overreaction to their negative news by purchasing shares. These patterns vary conditional on the information environment and news categories. My results suggest that CEOs can make the news salient via their trading pattern.

The second chapter uses staggered state-level bank deregulation events in the United States as exogenous shocks to investigate the effects of bank competition on bank liquidity creation at the state level. I document that state-level bank deregulation does not, on average, significantly affect state-level bank liquidity creation, while bank-level analyses demonstrate that enhanced bank competition decreases bank liquidity creation. In addition, I find that states and banks respond to the state-level deregulation events differently. My results suggest that the policy, which is applied to all heterogeneous banks and states in the same way, does not fit all.

In the third chapter, I examine how bank CEO debt incentives relate to bank liquidity creation. I find that higher CEO inside debt holdings are associated with lower bank liquidity creation, suggesting that CEOs with higher inside debt holdings adopt more conservative liquidity creation strategies. The result is driven by large banks, suggesting that CEOs in large banks manage banks more conservatively than CEOs in small banks, as their inside debt holdings increase. My results suggest that while regulators could increase bank liquidity creation by imposing lower CEO inside debt holding requirements, it could simultaneously make banks riskier. Debt-based compensation would be a double-edged sword for designing policy about bank liquidity creation and bank soundness.

ORIGINALITY STATEMENT

‘I hereby declare that this submission is my own work and to the best of my knowledge it contains no materials previously published or written by another person, or substantial proportions of material which have been accepted for the award of any other degree or diploma at UNSW or any other educational institution, except where due acknowledgement is made in the thesis. Any contribution made to the research by others, with whom I have worked at UNSW or elsewhere, is explicitly acknowledged in the thesis. I also declare that the intellectual content of this thesis is the product of my own work, except to the extent that assistance from others in the project's design and conception or in style, presentation and linguistic expression is acknowledged.’

Signed ……………………………………………..............

Date ……………………………………………..............

COPYRIGHT STATEMENT

Signed ……………………………………………..........................

Date ……………………………………………..............................

AUTHENTICITY STATEMENT

'I certify that the Library deposit digital copy is a direct equivalent of the final officially approved version of my thesis.'

Signed ……………………………………………..........................

Date ……………………………………………..............................

INCLUSION OF PUBLICATIONS STATEMENT

UNSW is supportive of candidates publishing their research results during their candidature as detailed in the UNSW Thesis Examination Procedure.

Publications can be used in their thesis in lieu of a Chapter if:

- The student contributed greater than 50% of the content in the publication and is the "primary author", ie. the student was responsible primarily for the planning, execution and preparation of the work for publication
- The student has approval to include the publication in their thesis in lieu of a Chapter from their supervisor and Postgraduate Coordinator.
- The publication is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in the thesis

Please indicate whether this thesis contains published material or not.

☒ *This thesis contains no publications, either published or submitted for publication*

☐ *Some of the work described in this thesis has been published and it has been documented in the relevant Chapters with acknowledgement*

☐ *This thesis has publications (either published or submitted for publication) incorporated into it in lieu of a chapter and the details are presented below*

CANDIDATE'S DECLARATION

I declare that:

- I have complied with the Thesis Examination Procedure
- where I have used a publication in lieu of a Chapter, the listed publication(s) below meet(s) the requirements to be included in the thesis.

Name	**Signature**	**Date (dd/mm/yy)**
Seungho Choi		**12/08/19**

Acknowledgements

First of all, I would like to express my sincere gratitude to my supervisors Professor Renée Adams and Dr. Chang Mo Kang at the School of Banking and Finance, UNSW Business School, the University of New South Wales (UNSW), for their invaluable guidance, support, and insightful discussions.

Also, I would like to thank Associate Professor Peter Pham, who has provided support and guidance as a Postgraduate Research Coordinator. I further thank the Graduate Research School (GRS) and UNSW Business School for providing administrative and financial support.

Lastly, I would like to express my deepest appreciation to my lovely wife, Kyungmi, and my parents, Hak-Won Choi and Jong-Sun Park, for their tremendous care and love that encouraged me to continue PhD degree when I faced difficulties. Without their support I would not have been able to complete this thesis.

Abstract

This thesis consists of three empirical studies about corporate finance and banking.

In the first chapter, I investigate how CEOs communicate with the market. CEOs have incentives to communicate with their investors after news releases if the market misinterprets the news. I examine how CEOs communicate with the market through their trading patterns. I find that CEOs are more likely to purchase shares after positive and negative news releases, suggesting that they want to confirm their positive news if the market underreacts to it and want to mitigate the market overreaction to their negative news by purchasing shares. These patterns vary conditional on the information environment, institutional ownership, and news categories. My results suggest that CEOs can make the news salient via their trading pattern.

The second chapter uses staggered state-level bank deregulation events in the United States as exogenous shocks to investigate the effects of bank competition on bank liquidity creation at the state level. I document that state-level bank deregulation does not, on average, significantly affect state-level bank liquidity creation, while bank-level analyses demonstrate that enhanced bank competition decreases bank liquidity creation. In addition, I find that states and banks respond to the state-level deregulation events differently. My results suggest that the policy, which is applied to all heterogeneous banks and states in the same way, does not fit all.

In the third chapter, I examine how bank CEO debt incentives relate to bank liquidity creation. I find that higher CEO inside debt holdings are associated with lower bank liquidity creation, suggesting that CEOs with higher inside debt holdings adopt more conservative liquidity creation strategies. The result is driven by large banks, suggesting that CEOs in large banks manage banks more conservatively than CEOs in small banks,

as their inside debt holdings increase. My results suggest that while regulators could increase bank liquidity creation by imposing lower CEO inside debt holding requirements, it could simultaneously make banks riskier. Debt-based compensation would be a double-edged sword for designing policy about bank liquidity creation and bank soundness.

Table of Contents

List of Figures

List of Tables

Abbreviations

CEO – Chief Executive Officer

CSS – Composite Sentiment Score

ESS – Event Sentiment Score

SEC – Securities and Exchange Commission

SOX – The Sarbanes-Oxley Act

TARP –Troubled Asset Relief Program

TIF – Thomson Reuters Insider Filing Database

U.S. – United States of America

Chapter 1:

Introduction

My thesis focuses on two main areas. First, I am interested in how CEOs communicate with their investors in the market. In the presence of information asymmetries between CEOs and other market participants, communication may reduce information asymmetries and facilitate the financial markets. On the other hand, communication may send a false positive signal to the market that benefits the information senders at the expense of the market participants. In my thesis, I try to examine how CEOs communicate with the market and why they have incentives to send the signal to the market. Insights from this line of research help to identify ways to correct the information in a timely manner.

Second, I am interested in the literature on the role of bank as a liquidity creator. I am particularly interested in the determinants of bank liquidity creation and its implications for policies. While there is a rich theoretical literature on bank liquidity creation, an empirical literature is still growing. In my thesis, I try to investigate what factors determine bank liquidity creation and why the relations are important from a social welfare perspective. This allows me to provide suggestions for policy makers.

In the first chapter, "Making News Salient", I examine how CEOs communicate with the market. CEOs have incentives to communicate with their investors after news releases if the market misinterprets the news. CEOs want to confirm their positive information if the market underreacts the positive news. This is because they have incentives to increase firm value. On the other hand, CEOs want to mitigate the market overreaction to the negative news if they have any information to correct the news. This is because they have incentives to avoid the undervaluation and have career concerns. I examine how CEOs communicate with the market through their trading patterns. Using CEO open-market purchase as a tool of communication, I find that CEOs are more likely to purchase shares after positive and negative news releases, suggesting that they want to confirm their positive news if the market underreacts to it and want to mitigate the market overreaction to their negative news by purchasing shares. These patterns vary conditional on the information environment, institutional ownership, and news categories. My results suggest that CEOs can make the news salient via their trading pattern.

In the second chapter, “Does Bank Competition Increase Bank Liquidity Creation? A State-Level Perspective,” I exploit staggered state-level bank deregulation events in the United States as exogenous shocks to investigate the effects of bank competition on bank liquidity creation at the state level. I document that state-level bank deregulation does not, on average, significantly affect state-level bank liquidity creation, while bank-level analyses demonstrate that enhanced bank competition decreases bank liquidity creation. In addition, I find that states and banks respond to the state-level deregulation events differently. My results suggest that the policy, which is applied to all heterogeneous banks and states in the same way, does not fit all.

In the third chapter, “CEO Inside Debt and Bank Liquidity Creation,” I examine how bank CEO debt incentives relate to bank liquidity creation. I find that higher CEO inside debt holdings are associated with lower bank liquidity creation, suggesting that CEOs with higher inside debt holdings adopt more conservative liquidity creation strategies. The result is driven by large banks and TARP recipients, suggesting that CEOs in large (TARP) banks manage banks more conservatively than CEOs in small (non-TARP) banks, as CEOs’ inside debt incentives increase. My results suggest that while regulators could increase bank liquidity creation by imposing lower CEO inside debt holding requirements, it could simultaneously make banks riskier. Debt-based compensation would be a double-edged sword for designing policy about bank liquidity creation and bank soundness.

Chapter 2:

Making News Salient

2.1 Introduction

CEOs have private information. When the private information is revealed to the market, the media play an important role in disseminating it to the market. However, information asymmetry still exists between CEOs and outside investors even after the news releases, so the investors may not be able to interpret the news correctly, even if the news media convey full information. This could result in a gap between the true information and the market reaction. CEOs are well aware of the information transfer between the media and the market, so they immediately recognize the informational gap after news releases. They have incentives to fill the gap by communicating with their investors if the communication can increase stock prices. However, this raises the following question: How do CEOs communicate with their investors?

One possible way that they can resolve the informational gap is to send a signal by trading their firm's shares after news releases. In this paper, I examine how CEOs communicate with their investors via their trading patterns after the information is revealed. CEOs could send a signal to the market about the news by trading their shares if the market misinterprets the news. They can see the informational gap and have incentives to fill it by communicating with the market if the market underreacts (overreacts) to positive (negative) information for several reasons, including the shareholders' wealth, career concerns, reputations, and their personal profits. In other cases, CEOs have no incentive to send signals to the market, as the market's underreaction to negative information and overreaction to positive information would be beneficial to their shareholders' wealth. Thus, I hypothesize that CEOs will correct the market's misperception about their news by purchasing shares in the open market when it is necessary to maximize shareholder value.

That is why, in this paper, I consider only CEO open market purchase as a tool of signaling. Communication through CEO open market sales can correct the information only when the company's stock is overpriced, suggesting that CEOs do have incentives to correct the mispricing because the signaling reduces shareholder value.

From the perspective of signaling theory, it is necessary that CEOs who do not have any superior information to the public information should not be able to mimic the trading patterns of CEOs with superior information. For example, CEOs could send the false positive information to pursue their own benefits. However, I can rule out this possibility because signaling through open market purchase is costly without true positive information. Since the mispricing should be fairly priced in the long run, the market can figure out whether the signal is true. CEOs should reckon for their incorrect signaling. This could have a negative effect on their wealth, job securities, and/or reputation. Thus, CEOs are reluctant to send the signal without any additional information.

In addition, because trading shares without the information is costly, the expected profitability of the open market purchase also could be an important part of incentives that encourages CEOs' communication with the market through their trading pattern. Since CEOs know the true information and analyze the informational gap well, they will perceive that the signaling is not costly with the additional information they have.

I first examine CEO trading patterns after news releases, regardless of the news tone. I find that CEOs are more likely to purchase shares in the open market after the news media releases firm-specific news. This suggests that CEOs may still have private information about the released news, and they want to provide an additional piece of information to the market. To be specific, the empirical evidence shows that an increase in media coverage stimulates CEOs to provide a signal to the market by purchasing their companies' shares. CEOs will have incentives to confirm their positive news in the case of the market underreaction to the positive news and to mitigate the market overreaction to the negative news by performing open market purchases. In contrast, firm-initiated press releases contain more explicit information than media-initiated news releases, so CEOs have less incentives to communicate with the market after corporate press releases.

Turning to news sentiment, I examine whether there are heterogeneous relations between the news tone and CEO trading pattern. I find empirical evidence that CEOs are more likely to purchase shares in the open market after positive and negative news releases. This suggests that CEOs may send the signal to the market to confirm the positive information if the market underreacts to the released positive news. In contrast, it also suggests that CEOs may send a signal to the market to mitigate the market overreaction to the negative news.

To understand the underlying economic channels driving the results, I first investigate the relations above depending on firms' information environment. To be specific, I define a transparent information environment based on analyst coverage and the SEC EDGAR filing search volume. Investors in firms with a transparent information environment would have better access to information than investors in firms with an opaque information environment. This means that information dissemination would be much more active in firms with transparent information channels and CEOs in these firms have a different incentive structure. To be specific, CEOs in firms with transparent information environments would have less incentives to send the signal to the market in the case of positive and negative news release because there is a lower likelihood of mispricing after the news releases under such an effective information dissemination. Using analyst coverage and the SEC EDGAR search volume as proxies for the transparent information environment, I find that CEOs are less likely to perform open market purchases in firms with intensive analyst coverage and active information acquisition after positive or negative news releases. The results are consistent with the hypothesis that effective information environment reduces CEOs' incentives to make the released news salient by purchasing their firms' shares in the open market.

Second, I examine whether intensive institutional ownership and types of institutional investors are associated with CEO trading patterns after news releases. Based on Bushee (2001), I classify institutional investors into three groups, such as dedicated, quasi-indexer, and transient institutions, in terms of their investment patterns. I expect that CEOs under the intensive institutional monitoring have stronger incentives to correct the market overreaction to the negative news because of career and reputation concerns. Consistent with the expectation above, I find that CEOs in firms with high institutional ownership, high dedicated, transient, and quasi-indexer ownership are more likely to send the signal to the market by purchasing shares in the open market. These suggest that CEOs under the good governance have stronger incentives to communicate with their investors after negative news releases.

Next, I examine whether the news category is associated with the CEO trading pattern after a news release. Following Wang, Zhang, and Zhu (2018), based on the RavenPack News Analytics category, I define news about revenue, earnings, analyst rating, and credit rating as hard news, and news about other topics is considered soft news. Hard news captures firms' fundamentals, whereas, soft news would be less value-relevant news. Thus, the market should pay more attention to hard news, with limited attention to soft news.

I hypothesize that CEOs have stronger incentives to communicate with their investors after negative hard news releases or positive soft news releases because the form of mispricing for these two cases is underpricing. I find a positive relation between positive soft news and CEO purchases, suggesting that CEOs are more likely to send the signal to the market because the market does not interpret the positive soft news well and could underreact to the news because of limited attention to soft news. I also find a positive relation between negative hard news coverage and CEO open market purchase. Because investors pay more attention to hard news than soft news, the market would overreact to the negative news, and CEOs have strong incentives to mitigate the market overreaction by sending a signal. On the other hand, the form of mispricing for negative soft news and positive hard news is overpricing. This means that CEOs would not have strong incentives to correct the mispricing because the overpricing enhances shareholders' value. Consistent with the expectation above, I find that CEOs are less likely to purchase shares as positive hard news or negative soft news release.

Next, I investigate the market reaction to CEO open market purchase. I estimate cumulative abnormal returns to capture the market reaction. I find that the market positively reacts to open market purchases followed by news coverage. Moreover, the news-related purchases outperform the other CEO purchase transactions. This suggests that the CEO trading pattern makes the news salient.

I also find a positive market reaction to the CEO's open market purchase, related to positive news coverage in the pre-transaction period, but the positive market reaction disappears for the CEO's open market purchase based on a [–5, –1] window. This suggests that such a CEO trading pattern would have significant credibility, but CEOs tend to react to the market underreaction to positive news and market overreaction to negative news differently.

In the case of a market underreaction, CEOs are more likely to react immediately, as they have additional positive information, which means that the cost of trading is relatively small. In contrast, I find a positive market reaction to negative news-related CEO purchase, and this result only holds for the [–5, –1] window specification, suggesting that CEOs tend to send the signal to the market through their trading pattern carefully in the case of the market overreaction because of the relatively high cost of trading.

To investigate whether the market reaction is solely related to the profitability of the CEO trading pattern, I explore the long-run market reaction to CEO open market purchase. Because the short-run market reaction is related to both news and CEO purchase transactions, I expect that the market will respond promptly to the additional information, and the news-related purchases will not outperform in the long run. I find empirical evidence that is consistent with my hypothesis.

Finally, I discuss alternative explanations for the empirical results of my paper. Some may argue that my results are driven by CEOs' incentive to exploit private information for increasing their personal wealth. To mitigate this concern, I investigate whether CEOs dispose their shares to realize profits as early as possible. I find that the average number of days between the purchase date and subsequent sale transaction is around 1,682 days, which is significantly longer than the restricted period of 180 days. In addition, I examine whether CEOs report their transactions as early as possible. They would report early if they intend to communicate with the market. I find that reporting gaps significantly decrease as cumulative news coverage increases. These results suggest that CEOs intend to communicate with their investors via their trading patterns.

The results are robust through extensive robustness checks, including analysis with different units of analysis, various time windows, analysis with alternative sentiment score, and sub-sample period analysis to avoid any bias caused by the pre-Sarbanes–Oxley Act (SOX) period. Also, to mitigate a concern about post-earnings announcement drift (PEAD), I examine the analysis, excluding observations within a month of the announcement, and the results are robust.

This paper contributes to the literature on insider trading. Previous studies have focused on insider trading before information releases (e.g., Ke, Huddard, and Petroni 2003; Fidrmuc, Goergen, and Renneboog 2006) and return predictability of insider trading (e.g., Seyhun 1986; Lakonishok and Lee 2001; Jeng, Metrick, and Zeckhauser 2003; Jenter 2005), but my study focuses on insider trading after information releases and considers insider trading as a way of communicating with the market. Accordingly, my paper adds to the literature on investor relations by exploring how CEOs communicate with their investors via their trading patterns. Past literature on investor relations has investigated the effects of investor relations (IR) activities on firms' visibility, media coverage, investor following, and firm value (e.g., Bushee and Miller 2012; Kirk and Vincent 2014; Karolyi and Liao 2017). In contrast to these studies, my paper suggests an insider-oriented communication method that can mitigate the information asymmetry between insiders and outside investors.

This paper also contributes to the literature on the role of media in accounting and finance. Previous studies suggest that the media play a monitoring role for identifying accounting and corporate frauds (e.g., Miller 2006; Dyck, Volchkova, and Zingales 2008; Dyck, Morse, and Zingales 2010), triggering firms' self-purification of their corporate governance quality (e.g., Joe, Louis, and Robinson, 2009), disciplining CEOs' compensation packages (e.g., Kuhnen and Niessen 2012), and mitigating insiders' profitability of insider trading (e.g., Dai, Parwada, and Zhang 2015; Rogers, Skinner, and Zechman 2016). I contribute to the literature by investigating CEOs' trading patterns conditional on media coverage and media sentiment.

The remainder of the paper is organized as follows. Section 2 of the paper provides a literature review. Section 3 describes the data on insider transactions, media coverage, as well as the other data I use in the paper. Section 4 provides the main results on the relationship between media and CEO trading pattern. Section 4 also explores whether information environment of the company and types of news play an important role in the relation between media and CEO trading pattern, the market reaction to CEO trading pattern, and whether CEOs have intentions to communicate with the investors. Section 5 concludes.

2.2 Literature Review

2.2.1 CEO Trading Patterns

Most previous literature on insider trading has focused on insider trading prior to public information release (e.g., Ke, Huddard, and Petroni 2003; Fidrmuc, Goergen, and Renneboog 2006). In addition, most previous studies have examined whether insiders exploit private information to realize profits when they trade shares of firms with which they are affiliated (e.g., Seyhun 1986; Lakonishok and Lee 2001; Jeng, Metrick, and Zeckhauser 2003; Jenter 2005).

Distinct from insider purchases, insider sales are not informative. As previous studies suggest, insiders tend to dispose their shares for diversifying their wealth portfolios (e.g., Lakonishok and Lee 2001; Jenter 2005). In addition, insiders would be reluctant to sell the shares because of litigation risk, even though private information motivates the sales.

In contrast to previous studies, I focus on CEO trading patterns after news releases. Two exceptions are Kolasinski and Li (2010) and Sivakumar and Waymire (1994). Kolasinski and Li (2010) examine insider trading patterns after public information releases, representing the earnings announcement. They find that insiders purchase shares after good earnings surprises and sell shares after bad earnings surprises. The results suggest that managers have private information about their companies' stock prices, and their trading patterns are informative in terms of profitability. Sivakumar and Waymire (1994) also investigate insider trading after earnings announcement and find that insiders tend to purchase shares after bad earnings announcements and dispose shares after good earnings announcements, indicating that insiders could exploit the market overreaction to the earnings news to pursue the profitability. However, different from this study, my study focuses on all firm-specific news and finds that the main results are robust even after excluding earnings-related news, including earnings announcements. This suggests that my results are not driven by PEAD.

There is a lack of studies about the determinants of CEO share trading. There may be several reasons why CEOs time their share transactions, and the profitability of this trading does not seem to be the only reason. Thus, in this paper, I explore how CEOs communicate with their investors using their open market share-trading pattern to fill a gap in the literature.

2.2.2 Media in Finance

There are several studies regarding the effects of media coverage and media sentiment in finance and accounting. From the perspective of information dissemination, the media help mitigate uncertainty in the capital market. They provide the market with both existing and new information. Previous studies have suggested that the information affects stock prices and stock returns (e.g., Bushee, Core, Guay, and Hamm 2010; Fang and Peress 2009; Huberman and Regev 2001; Peress 2014). In addition, past literature has documented the role of media in corporate governance. Miller (2006), Dyck, Volchkova, and Zingales (2008), and Dyck, Morse, and Zingales (2010) report that news coverage helps in identifying accounting and corporate frauds. In addition, studies have revealed the media's disciplinary effects; for example, Joe, Louis, and Robinson (2009) show that negative news coverage on firms’ corporate governance makes firms improve their corporate governance quality by replacing their CEO and/or chairman and changing the board structure. This suggests that the negative tone of news could trigger firms’ self-purification.

Core, Guay, and Larcker (2008) and Kuhnen and Niessen (2012) find mixed empirical evidence on the effects of media coverage on CEO compensation policy. Core, Guay, and Larcker (2008) find that the negative media coverage does not affect firms’ executive compensation policy, but Kuhnen and Niessen (2012) stated that CEO compensation–related news coverage affects firms’ compensation policies.

Dai, Parwada, and Zhang (2015) and Rogers, Skinner, and Zechman (2016) examine the effects of the media on insider trading. The former explores the role of media on the profitability of insider trading, with the study finding that news coverage negatively affects the profitability of insider trading by disseminating news to the market because of the media’s monitoring function. The latter study examines the effects of news releases on the capital market, finding that insider trading–related news affects stock prices and trading volume.

Despite the studies mentioned above, there is not enough research on insider trading patterns after news releases. The previous studies concerning the relationship between media and insider trading have focused on the profitability of insider trading after news releases. In addition, most studies have concentrated on whether insiders utilize private information to realize profits in their personal wealth, but in this paper, my focus is on how insiders use their trading patterns as a means of communicating with their investors.

There is also a lack of research regarding the different effects of news tones. I examine whether news sentiment is associated with CEO trading patterns to tease out the heterogenous effects of positive and negative news under different information environments. The evidence in this paper contributes the literature on the determinants of insider trading patterns.

2.3 Data

I compile a wide-ranging data from a variety of sources. I mainly collect event-based transaction-level CEO insider trading data from the Thomson Reuters Insider Filing database. For media coverage and sentiment data, I collect the data from RavenPack News Analytics, which is widely used by research papers in accounting and finance. In addition, I obtain balance sheet data and income statement accounting data from Standard & Poor's Compustat Fundamentals, and stock prices and market capitalization data are from the Center for Research in Security Prices (CRSP). In addition, I collect CEO compensation data from Compustat ExecuComp. Institutional ownership data is collected from Thomson Reuters Institutional (13f) Holdings, and analyst data is obtained from the Institutional Brokers Estimate System (I/B/E/S).

To qualify for inclusion in the sample, a firm must be listed on NASDAQ, NYSE, and AMEX stock markets and also be covered by the Thomson Reuters Insider Filing Database. Additionally, I eliminate observations with missing stock prices, stock returns, and number of shares outstanding.

To construct firm-person-day-level data, I start with the CRSP Daily dataset and Compustat Fundamentals annual data. I only include sample firms that have at least one CEO transaction record and at least one news coverage observation during the firms' life. Because of the shorter data coverage of RavenPack, the sample period of the final dataset is from 2000 to 2016. The final dataset consists of 5,339 sample firms, and total number of observations is 13,873,842.

2.3.1 CEO Trading Measures

To construct the CEO insider trading measures, I collect CEO stock transaction records from the Thomson Reuters Insider Filings database. I match the data with the CRSP database to verify whether the transaction prices posted on the TIF database are correct. Following Heron and Lie (2007) and Bebchuk, Grinstein, and Peyer (2010), I define an insider as a CEO if she is classified either as the CEO or president of the company on the TIF database.

To identify CEO trading patterns, I only retain all open market purchases and sales by CEOs of publicly traded firms. Shares acquired through stock awards and trades with employers are excluded from my data. The TIF database provides transaction codes and acquisition/disposition indicators. To construct CEO share trading variables, I only retain transaction codes with appropriate acquisition/disposition flags, such as observations with transaction code "P" and acquisition flags and observations with transaction code "S" and disposition flags. In addition, I drop observations representing amendments of prior records to avoid double-counting transactions. I check transactions with multiple amendments using the Amendment Concordance of the TIF data and drop all transactions with multiple amendments. This is because I do not know whether the amendment is related to omitted transactions or inaccurate records.

Because my study investigates how CEOs communicate with their investors by trading their shares, share transactions regarding routine stock-based compensation and/or company disposition are not suitable for capturing individual CEOs' trading patterns, which send signals to the market, under information asymmetry. *Buy* is an indicator variable that is equal to 1 if the CEO performs open market stock purchase within a specified date, and *Sell* is an indicator of daily open market sales transactions.

The TIF database provides ample information on insider stock trading and derivative trading, as well as various insiders' position information. However, I have several concerns with using TIF database. First, the data are too noisy to retain all the transactions. Thomson Reuters provides a cleanse indicator that indicates the level of accuracy of each transaction-level data.[1] I eliminate transactions without transaction price information. I also remove transactions that have lower transaction prices than the lowest trading price during the day or higher transaction prices than the highest trading price during the day.

The second concern relates to identifying each insider's position. Although the Thomson Reuters Insider Filing data provide four role code variables, the information about the insider's role is not perfectly correct. Even when I match CEOs in the TIF database to CEOs in the Execucomp data, I can see some discrepancies between the two datasets. This is why I adopt a name-matching process to identify CEOs between Thomson Reuters Insider Filing data and Execucomp. To mitigate the concern about missing CEOs with no open market transaction records in the TIF data, I include both CEOs who have at least one open market share transaction record in TIF data and all Execucomp CEOs.

2.3.2 Media Coverage Measures

Following previous studies investigating the effects of media or the determinants of media coverage and/or media sentiment, I construct media coverage and media sentiment variables. Since the RavenPack News Analytics comprises event-based data, I consider the number of news coverage as zero if there is no news observation in a day.

Following Dai, Parwada, and Zhang (2015), I use the number of news coverage

[1] To have credible transaction records, I only keep transactions with cleanse codes of "R," "H," "C," "L," or "I."

as one of the key proxies for media coverage. In contrast to their measure, which represents the amount of news coverage scaled by 100, I employ the log transformation to mitigate skewness in the key variables. However, I also follow these researchers' original news coverage measures for the robustness checks. Because the unit of analysis of this paper is the transaction-date level, I construct the key news coverage variable, which is the natural logarithm of 1 + the cumulative number of news coverage items in certain windows. To incorporate news momentum effects, I also construct the news coverage variables that have only pre-period news coverage.

In addition to news coverage measures, I construct the news sentiment variables indicating three different tones of news. Based on RavenPack News Analytics' two main news sentiment scores, the Event Sentiment Score (ESS) and Composite Sentiment Score (CSS), I identify the tone of each news item.

The ESS represents the news sentiment for a given company by measuring diverse proxies sampled from the news. To determine the sentiment score, financial and economic experts, who are highly experienced in the firm's industry, categorize and rate each firm-specific news event. Based on the categorized and rated firm-specific news, RavenPack's unique algorithm assigns a score ranging from 0 to 100. In this setting, scores above 50 represent positive sentiment and scores below 50 represent negative sentiment. A sentiment score of 50 signifies neutral sentiment. In addition to the expert consensus survey data, the algorithm considers a wide range of factors, including the emotional factor, which is based on words and phrases in the news; weather and climate factor; analyst rating factor; credit rating factor; fundamental comparison factor, which analyzes numerical differences between the actual and estimated values in various financial and economic indicators and/or figures and values stated in the news; and casualties factor.

The CSS represents the news sentiment for a given story by combining three sentiment analysis methodologies, as follows: the traditional tagging methodology, expert-trained classifier methodology, and market response methodology. First, the traditional tagging methodology analyzes news stories and identifies positive and negative words and phrases in the news about global equities and earnings evaluations. Second, the expert consensus methodology analyzes news about mergers, acquisitions, takeovers, and corporate action announcements and short commentary and editorials on global equity markets. Finally, the market response methodology identifies and maps individual words or word combinations in the news headlines to the price effects on the stocks of the companies mentioned in the headline. Using intraday tick data from 100 large-cap stocks, the methodology measures the relative volatility, which is the volatility divided by the mean of volatilities of all companies during the same time periods of the mentioned stocks' prices in hours following story arrival to see how markets respond to the news in the short term. Based on the methodologies, RavenPack suggests that news with a CSS above 50 is positive news, news with a CSS below 50 is negative news, and news with a CSS equal to 50 is neutral news.

Although the ESS and CSS are positively correlated at the 1% significance level, it is possible to have some conflicts between the two sentiment scores. According to the RavenPack News Analytics user manual, the two measures generally have the same sentiment direction, but they could have different directions because each measure captures different perspectives on sentiment for the same news. Since the ESS utilizes a category-based algorithm and represents the news sentiment for a given company, ESS is independent from CSS, which depends on five sentiment scores and represents the news sentiment for a given story.

Based on the ESS and CSS, I classify the news into positive, negative, and neutral news. To measure news tone, I construct ratios of positive (negative) news, defined as the number of positive (negative) news items within certain windows normalized by the number of news coverage items within the windows. In addition, I construct a natural logarithm of the number of positive (negative) news items as proxies for media sentiment. Furthermore, I construct indicator variables of positive (negative) news within certain windows. For the robustness checks, I also use the sentiment score as a proxy for media sentiment. Following Bushman, Williams, and Wittenberg-Moerman (2016), I use the average media sentiment score across all firm-specific news articles published over various periods. To be specific, I use the average ESS and average CSS over the past 2-, 3-, 5-, and 10-day periods. Before calculating the averaged sentiment scores, I apply a linear transformation to each individual sentiment score and define the media sentiment as Sentiment Score – 50, scaled by 50.

2.3.3 Control Variables

I control for several firm characteristics that could affect CEOs' trading behavior. Firm size (*Ln(Size)*) is the natural logarithm of the firm's market capitalization. Market-to-book (*MTB*) is the market-to-book ratio at the prior year-end. Stock returns (*Return*) are stock returns over the prior 12 months, calculated using a monthly rolling window. I also control for the Amihud (2002) illiquidity measure (*Illiquidity*) and idiosyncratic risk (*IVOL*), which is the stock's annualized residual return from a regression of daily stock returns on Fama–French's three factors during the past year. To control for news size effects, I include news coverage (*LN(News Coverage)*), which is the natural logarithm of 1 + news coverage in certain windows. To control for the information environment, I add analyst coverage and institutional ownership variables to some specifications. A table of variable definition is presented in Appendix A.

2.3.4 Summary Statistics

Summary statistics are presented in Tables 1 and 2. Panel A of Table 1 shows the daily-level summary statistics on news, CEO trading, and financial variables. I set three different windows to construct these variables, namely [–2, –1], [–3, –1], and [–5, –1], based on average time spent disseminating a unique news item.[2] I define positive and negative news based on the CSS, which is one of the most comprehensive media sentiment scores, provided by RavenPack News Analytics. I also construct the media variables based on the ESS as alternative media variables for robustness tests. However, I only report cumulative news coverage variables based on the [–5, –1] window for simplicity. I report summary statistics using the [–2, –1] and [–3, –1] windows in Table 2C in Appendix.

For the perspective of news sentiment, the distribution of news sentiment is different between the ESS and CSS. Figure 1 and Panel A of Table 2A show the trend in the annualized number of news coverage items and trend in news coverage by news tone based on the ESS and CSS during the sample period. The results show that news coverage increases over time, suggesting that the amount of information that investors can access also increases over time. In addition, these findings show that positive news occupies the largest portion, which is around 50% on average, based on the ESS. However, Figure 1 and Panel A of Table 2A show that neutral news occupies the largest portion, around 45% on average, based on the CSS. However, there is no significant change in the portions of positive, negative, and neutral news.

[2] RavenPack News Analytics considers an additional news item as a unique news item if the time lag between the first unique news release and the additional new release is over 24 hours. Based on its methodology, the average time spent disseminating each unique news is about 2 days. Thus, I use relatively short time windows, such as [–2, –1], [–3, –1], and [–5, –1].

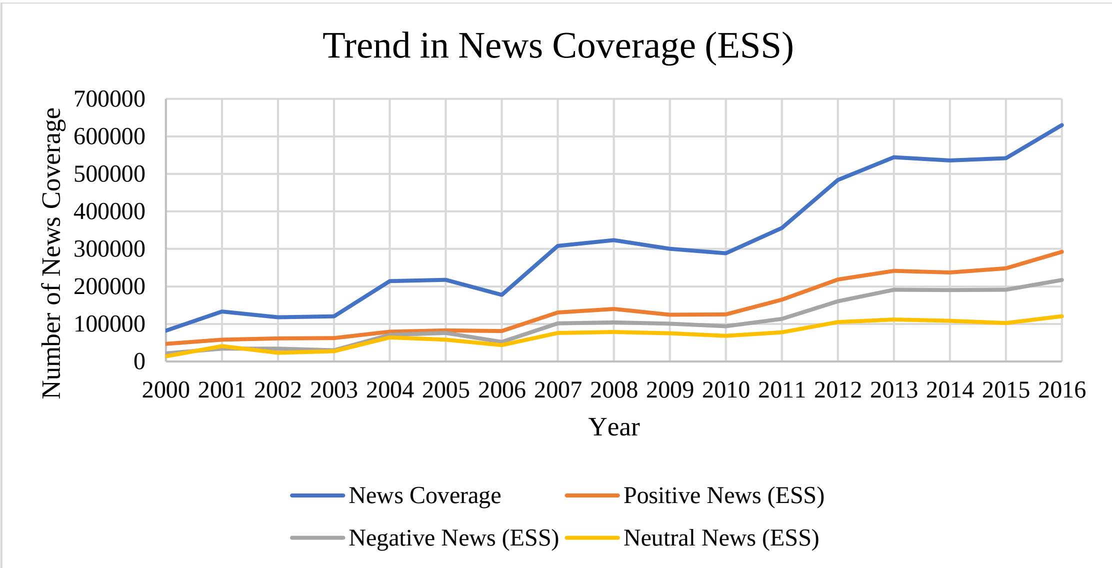
In Panel B of Table 2A, I present the trend in news coverage by news category. Following the RavenPack News Analytics categorization, I separate news into two groups, namely hard news and soft news. I define more value-relevant news topics, such as revenue, earnings, analyst rating, and credit rating, as hard news, while other topics are considered as soft news. Because hard news is directly related to firms' fundamentals, there will be sufficient investor attention to hard news but relatively limited attention to soft news.

Panel B of Table 2A shows that there is much more soft news coverage than hard news coverage during my sample period. Soft news occupies about 70% on average. This suggests that there is a relatively high probability of suffering a market underreaction to the positive news, such that CEOs would need to confirm the positive information by purchasing their shares. This is because it is easier to overlook soft news than hard news from the perspective of outside investors.

Panel D of Table 1 shows the trend in CEO trading patterns. There are more open-market share purchases during and after the recent financial crisis from 2007 to 2009 and the dot-com bubble in 2000 than in normal periods, in terms of both quantity and proportion. These results suggest that CEOs may have more incentive to communicate with the market when companies suffer financial distress and their career concerns are exacerbated.

Figure 2.1 Trend in News Coverage from 2000 to 2016

This figure shows the annualized number of news coverage trend from 2000 to 2016 and the trend in tone of news coverage from 2000 to 2016. News coverage data is collected from RavenPack News Analytics. I identify positive, negative, and neutral tone of news based on either the event sentiment score (ESS), which indicates how firm-specific news events are categorized and rated as having a positive or negative effect on stock prices by experts with extensive experience and backgrounds in linguistics, finance, and economics, or the composite sentiment score (CSS), which indicates how the market responds to news articles and is estimated based on stock price reactions, which are empirically modeled using intraday data from a portfolio of approximately one hundred large-cap stocks. The sentiment score has a value ranging between 0 and 100, with a value above (or below) 50 indicating the positive (or negative) sentiment of a given news event, whereas a value of 50 represents a neutral sentiment. More detailed information about the trend in news coverage is reported in Appendix.



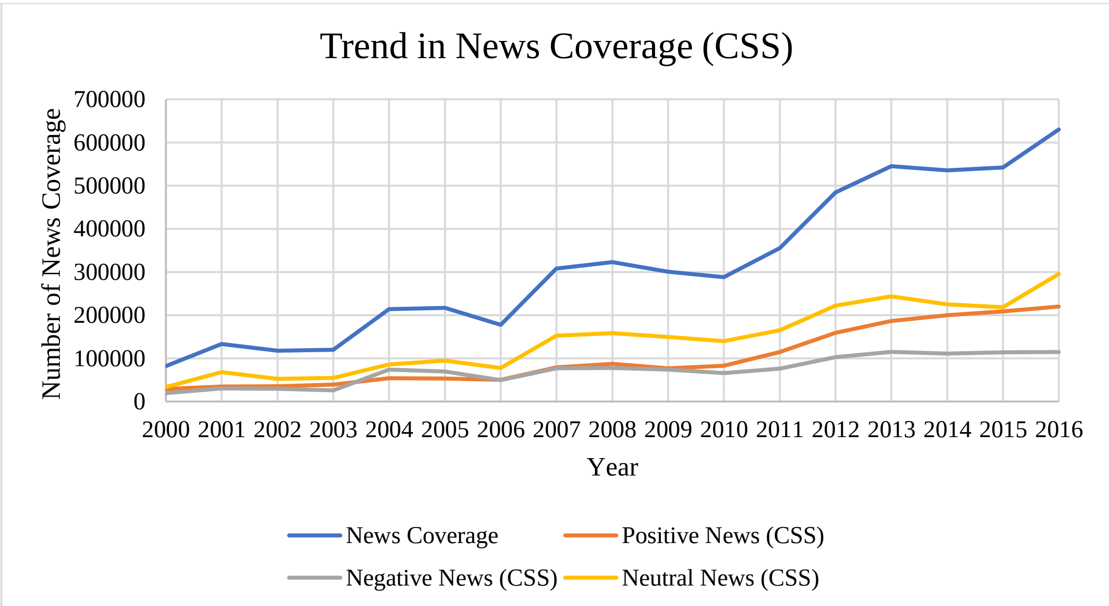
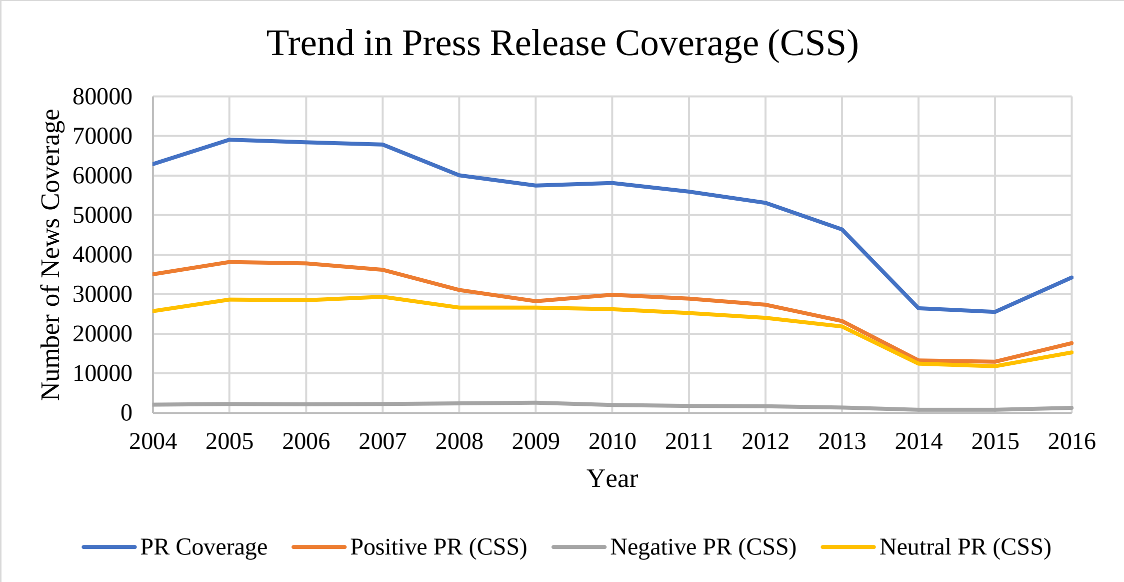


Figure 2.2 Trend in Corporate Press Release Coverage from 2004 to 2016

This figure shows the annualized number of corporate press release coverage trend from 2000 to 2016 and the trend in tone of corporate press release coverage from 2000 to 2016. Press release coverage data is collected from RavenPack News Analytics. I identify positive, negative, and neutral tone of news based on either the event sentiment score (ESS) or the composite sentiment score (CSS). The sentiment score has a value ranging between 0 and 100, with a value above (or below) 50 indicating the positive (or negative) sentiment of a given press release event, whereas a value of 50 represents a neutral sentiment. More detailed information about the trend in corporate press release coverage is reported in Appendix.



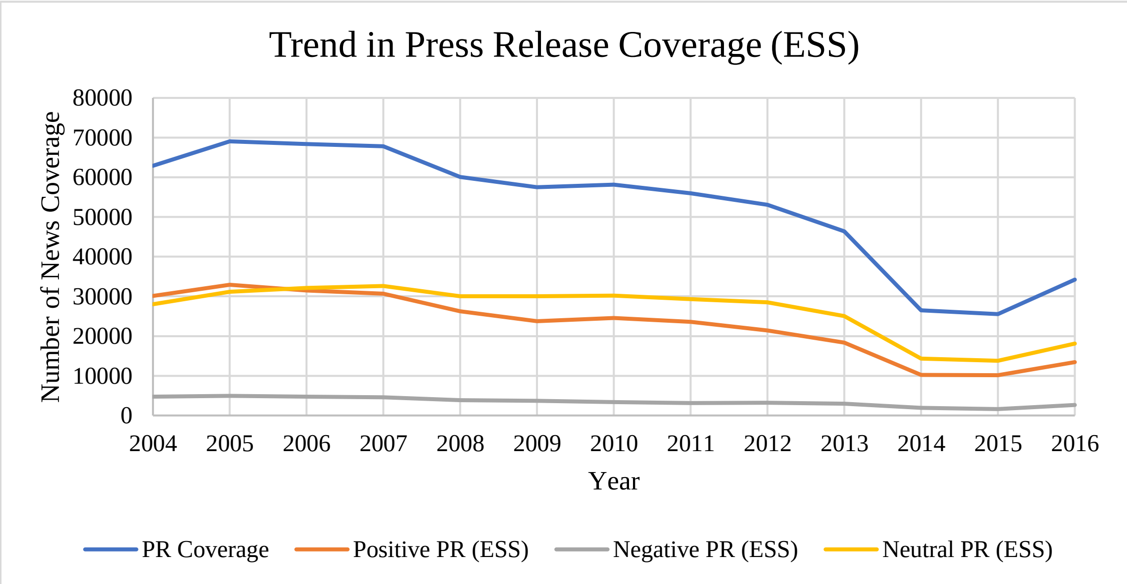


Table 2.1 Summary Statistics

This table presents the summary statistics about news, CEO trading pattern, firm characteristics, and cumulative abnormal returns variables. The sample consists of 5,339 firms from 2000 to 2016. Panel A presents daily-level summary statistics, and Panel B presents daily-level summary statistics by CEO trading direction. Panel C shows within- and between-firm variations in news variables. Detailed information about variables are available in Appendix.

Panel A. Summary Statistics: Daily-level

News Variables	N	Mean	SD	P25	P50	P75
LN(News)	13,824,801	0.451	0.658	0	0	0.693
LN(Pos_News)	13,824,801	0.182	0.406	0	0	0
LN(Neg_News)	13,824,801	0.249	0.473	0	0	0
LN(Neu_News)	13,824,801	0.140	0.348	0	0	0.693
LN(Hard_Pos)	13,824,801	0.060	0.245	0	0	0
LN(Hard_Neg)	13,824,801	0.043	0.206	0	0	0
LN(Hard_Neu)	13,824,801	0.060	0.257	0	0	0
LN(Soft_Pos)	13,824,801	0.135	0.336	0	0	0
LN(Soft_Neg)	13,824,801	0.104	0.289	0	0	0
LN(Soft_Neu)	13,824,801	0.200	0.416	0	0	0

CEO Trading Variables	N	Mean	SD	P25	P50	P75
Buy	13,824,801	0.002	0.044	0	0	0
Sell	13,824,801	0.007	0.083	0	0	0

(Continued from the previous page)

Firm-Characteristics	N	Mean	SD	P25	P50	P75
LN(Size)	13,687,981	13.019	2.032	11.560	12.930	14.340
MTB	13,567,744	2.053	2.534	1.0540	1.3840	2.1710
Return	13,687,981	0.013	0.060	-0.0105	0.0106	0.0316
Illiquidity	13,778,902	0.279	0.728	0.0011	0.0097	0.1230
IVOL	13,308,613	0.440	0.381	0.2180	0.3390	0.5420
Earnings Month	13,824,801	0.333	0.471	0	0	1
Dividend Month	13,824,801	0.127	0.332	0	0	0
Analyst Coverage	11,711,804	2.960	1.184	2.1970	3.0910	3.8290
Institutional Ownership	8,190,712	0.556	0.311	0.2870	0.5970	0.8090
LN(Search Volume)	11,194,064	3.729	2.040	2.3026	3.8067	5.3753
Cumulative Search (12 months)	11,194,064	44840	91092	3381	11549	53810

Cumulative Abnormal Returns	N	Mean	SD	P25	P50	P75
CAR[0, 1]	121,400	0.0044	0.055	-0.0168	0.0007	0.0205
CAR[0, 2]	121,400	0.0056	0.065	-0.0201	0.0012	0.0254
CAR[0, 3]	121,400	0.0065	0.074	-0.0232	0.0015	0.0293
CAR[0, 4]	121,400	0.0072	0.080	-0.0259	0.0017	0.0328
CAR[0, 5]	121,400	0.0076	0.086	-0.0284	0.0020	0.0361
CAR[0, 10]	121,400	0.0100	0.112	-0.0373	0.0038	0.0495
CAR[0, 20]	121,400	0.0126	0.149	-0.0515	0.0067	0.0706
CAR[0, 30]	121,400	0.0152	0.187	-0.0635	0.0095	0.0872
CAR[0, 40]	121,400	0.0175	0.217	-0.0734	0.0118	0.1020
CAR[0, 50]	121,400	0.0196	0.248	-0.0821	0.0133	0.1140
CAR[0, 60]	121,400	0.0216	0.268	-0.0921	0.0150	0.1270

Panel B. Summary Statistics: Purchase & Sale

	Purchase				Sale			
News Variables	N	Mean	SD	P50	N	Mean	SD	P50
LN(News)	26,978	0.6270	0.7330	0.6930	95,886	0.8470	0.8100	0.6930
LN(Pos_News)	26,978	0.3800	0.5510	0	95,886	0.2760	0.5220	0
LN(Neg_News)	26,978	0.1750	0.4130	0	95,886	0.3400	0.5100	0
LN(Neu_News)	26,978	0.2390	0.4670	0	95,886	0.5140	0.6280	0
LN(Hard_Pos)	26,978	0.0878	0.2900	0	95,886	0.1260	0.3750	0
LN(Hard_Neg)	26,978	0.1110	0.3430	0	95,886	0.0515	0.2240	0
LN(Hard_Neu)	26,978	0.1110	0.3420	0	95,886	0.1070	0.3520	0
LN(Soft_Pos)	26,978	0.3140	0.5020	0	95,886	0.1820	0.3960	0
LN(Soft_Neg)	26,978	0.0779	0.2480	0	95,886	0.2990	0.4790	0
LN(Soft_Neu)	26,978	0.1450	0.3460	0	95,886	0.4350	0.5760	0
Firm-Characteristics	N	Mean	SD	P50	N	Mean	SD	P50
LN(Size)	26,617	11.8700	1.7650	11.7000	95,542	13.9300	1.6900	13.7900
MTB	26,160	2.0280	2.7360	1.2220	94,953	3.0310	3.8120	2.0860
Return	26,617	-0.0077	0.0647	-0.0062	95,542	0.0312	0.0624	0.0235
Illiquidity	26,801	0.5870	1.0190	0.0946	95,777	0.0452	0.2330	0.0023
IVOL	25,408	0.5940	0.4440	0.4690	95,519	0.4000	0.3090	0.3170
Earnings Month	26,978	0.4090	0.4920	0	95,886	0.3250	0.4680	0
Dividend Month	26,978	0.1100	0.3130	0	95,886	0.1070	0.3090	0
Analyst Coverage	19,916	2.4260	1.1560	2.4850	91,595	3.3130	1.0490	3.4010
Institutional Ownership	15,889	0.4010	0.3000	0.3490	55,596	0.6900	0.2680	0.7450

Cumulative Abnormal Returns (CAR)	N	Mean	SD	P50	N	Mean	SD	P50
CAR[0, 1]	26,155	0.0131	0.0833	0.0054	95,286	0.0020	0.0458	-0.0001
CAR[0, 2]	26,155	0.0197	0.0969	0.0096	95,286	0.0017	0.0536	-0.0003
CAR[0, 3]	26,155	0.0254	0.1090	0.0127	95,286	0.0014	0.0609	-0.0004
CAR[0, 4]	26,155	0.0285	0.1170	0.0141	95,286	0.0013	0.0671	-0.0006
CAR[0, 5]	26,155	0.0311	0.1240	0.0156	95,286	0.0012	0.0725	-0.0005
CAR[0, 10]	26,155	0.0409	0.1540	0.0218	95,286	0.0016	0.0955	0.0003
CAR[0, 20]	26,155	0.0538	0.1950	0.0296	95,286	0.0014	0.1320	0.0022
CAR[0, 30]	26,155	0.0669	0.2300	0.0389	95,286	0.0011	0.1710	0.0036
CAR[0, 40]	26,155	0.0760	0.2610	0.0448	95,286	0.0015	0.2010	0.0049
CAR[0, 50]	26,155	0.0864	0.2860	0.0508	95,286	0.0014	0.2340	0.0055
CAR[0, 60]	26,155	0.0966	0.3130	0.0594	95,286	0.0011	0.2500	0.0060

Panel C. Within- and Between-Firm Variations in News Variables

Variable	Overall	Between	Within
LN(News) [-5, -1]	0.657	0.311	0.573
LN(Pos_News) [-5, -1]	0.406	0.153	0.373
LN(Neg_News) [-5, -1]	0.347	0.120	0.325
LN(Neu_News) [-5, -1]	0.472	0.202	0.422
LN(Pos_Hard) [-5, -1]	0.245	0.050	0.240
LN(Neg_Hard) [-5, -1]	0.205	0.028	0.203
LN(Neu_Hard) [-5, -1]	0.256	0.037	0.254
LN(Pos_Soft) [-5, -1]	0.336	0.130	0.307
LN(Neg_Soft) [-5, -1]	0.289	0.110	0.266
LN(Neu_Soft) [-5, -1]	0.416	0.188	0.365

Panel D. Trend in CEO Trading Pattern

This table presents number of CEO share transactions per year. The sample consists of 5,339 firms from 2000 to 2016. I only include open market transactions.

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Total	7,276	7,838	7,449	7,319	8,305	8,386	8,393	8,452	7,571	5,932	5,871	6,667	6,908	7,423	7,256	7,346	6,362
Buy	2,627	1,829	2,089	1,254	999	1,100	1,150	1,622	2,935	2,055	924	1,766	1,603	937	1,353	1,904	1,561
(%)	36.11	23.34	28.04	17.13	12.03	13.12	13.70	19.19	38.77	34.64	15.74	26.49	23.20	12.62	18.65	25.92	24.54
Sale	4,649	6,009	5,360	6,065	7,306	7,286	7,243	6,830	4,636	3,877	4,947	4,901	5,305	6,486	5,903	5,442	4,801
(%)	63.89	76.66	71.96	82.87	87.97	86.88	86.30	80.81	61.23	65.36	84.26	73.51	76.80	87.38	81.35	74.08	75.46

2.4 Empirical Results

2.4.1 CEO Trading Patterns after News Release

In this section, I report on my empirical analysis of the relationship between media and CEO trading patterns. First, I focus on whether news coverage is associated with insider trading patterns. I estimate the linear probability model outlined below.

$$LPM: Pr(Y = 1 | X_1, X_2, \dots, X_k) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \mu_i + v_t + \varepsilon_{it} \quad (1)$$

Dependent variables for the linear probability model are CEO share trading indicator variables, such as *Buy* and *Sell*. In the model, μ_i signifies each firm's time-invariant specific effect and v_t represent that year's specific effect. X_{it} is a set of explanatory variables at the firm level at time t-1 including media variables and control variables, and ε_{it} is an error term. Standard errors are clustered by both firm and year.

I use linear probability models to include firm fixed effects.[3] Previous studies regarding the effects of media in finance have usually controlled for industry fixed effects because Solomon and Soltes (2012) suggest that industry-specific effects explain a significant proportion of the variation in firm media coverage. However, according to the within- and between-firm variation analysis in Panel C of Table 1, we can see that most variations in media variables come from the within-firm standard deviation. Thus, I include firm fixed effects in the main regressions. For the robustness check, I include

[3] Greene (2004) suggests that the nonlinear fixed effects model has disadvantages in controlling for a vast number of dummy variables and the coefficients for the dummy variables may be estimated without the necessity of inverting a large matrix. In my sample, the number of sample firms is 5,339, which is large enough to obtain biased coefficients. Thus, in this paper, I include linear probability model specifications to control for firm fixed effects.

industry fixed effects instead of firm fixed effects, and the results are robust.

Table 2 lists specifications examining the relationship between news coverage and CEO open market purchase trading patterns. As the prior literature suggests, enhanced news coverage may increase CEO open market purchases, as the market can either underreact or overreact to news and CEOs would want to correct the information. The market may underreact to positive news. In this case, the CEO has the incentive to send a signal to the market by purchasing company shares, as the CEO knows that the released positive news does not cover all the positive aspects of the news. Although sending the signal through open market purchase is costly, CEOs are willing to do so under the information advantage to confirm the positive information. CEOs can also send signal if the market overreacts to negative news. Because of the nature of negative news, CEOs should expect negative returns on her open market purchase in the short run. Even in this case, the CEO may have incentives, such as monitoring, career concerns, reputation, and so on, to send the signal to mitigate the market overreaction to the negative news.[4]

In Table 2, I find that news coverage positively relates to CEO open market purchases. The empirical evidence supports the expectation I outlined above. The results are consistent for all specifications using various time windows. In the untabulated results,

[4] Different from earnings announcement studies, it is quite difficult to measure the market under- and over-reaction to each individual firm specific news event because I do not have appropriate benchmarks. Thus, I assume that the market underreacts (overreacts) to released positive (negative) news if CEOs send a signal to the market after the news releases by purchasing their company's shares in the open market. This is because CEOs have incentives to send the signal only in the cases of the market undervaluation. If the investors underreact (overreact) to negative news (positive news), then the firm's stock price is overvalued. In these cases, CEOs may not want to send a signal to correct the market overvaluation.

I control for industry-specific time-invariant characteristics by including the two-digit Standard Industrial Classification (SIC) code, and the results remain unchanged. In addition, I run a transaction-level analysis using open market transactions. Among all the open market transactions, I find that CEOs are more likely to purchase shares and less likely to sell shares, and the results are robust to different sets of fixed effects. The transaction-level analysis allows me to include CEO fixed effects, because Thomson Insider Filing Database provides a unique person identification number. I report the results in Panel A of Table 3A.

Different from news coverage, the information content of corporate press release is initiated by firms. The extent of information dissemination would be different between news releases and firm-initiated press releases. This is because the firm-initiated press releases provide more explicit information than news releases on average. Therefore, CEOs would not send the signal to the market by purchasing shares in the open market after the firm-initiated press releases. In Table 3, I find that CEOs are less likely to purchase shares after corporate press releases, suggesting that CEOs would not have incentives to make the press release salient by sending the signal. Coefficients on cumulative news coverage variables are robust even after controlling for cumulative press release. For all analysis in this paper, I also run the regressions including corporate press release variable, and the results are robust. However, in this paper, I only report the regression results without corporate press release as a control variable in subsequent sections because the press release data is only available from 2004.

In this paper, I only investigate CEO open market purchase as a signaling mechanism. Insider sale transactions would be less informative because insiders tend to sell shares to diversify their wealth portfolio. Also, CEOs have no incentive to send the signal to the market through their sale transactions because they would not want to send the signal that can adversely affect their firm value. For example, the firm value could decrease if CEOs correct the market underreaction to firm's negative news or the market overreaction to firm's positive news. In Panel B of Table 3A, I examine the relation between news coverage and CEO open market sales. Results show that CEOs are more likely to sell shares after news releases, suggesting that CEOs want to diversify their wealth portfolio when there is no litigation risk. Thus, their share disposal in the open market do not provide any additional information to the market.

The above results cannot show whether CEOs respond to the market underreaction or overreaction. Thus, I divide news coverage into positive, neutral, and negative news coverage in the subsequent analysis.

In Table 4, I regress the CEO trading pattern on news tone, including positive news coverage, negative news coverage, neutral news coverage, and various control variables. The coefficients on positive and negative news variables are all positive and statistically significant in Columns 1–6. The magnitude of coefficients is different between positive news and negative news coverage, suggesting that CEOs tend to send the signal to the market more carefully in the case of a market overreaction to negative news than in the case of a market underreaction to positive news, as sending the signal is costly without additional information and negative news would result in negative returns. The results are robust to alternative sets of fixed effects, such as industry fixed effects; alternative measures of news tone; and various time windows.

For CEO share sales, I find consistent results with the analysis on the relation between cumulative news coverage and CEO trading patterns. Panel B of Table 4A shows that CEOs are less likely to sell shares in the open market after positive news releases. This suggests that CEOs do not want to take any risks regarding illegal informed trading. Even though the underlying information is already revealed to the market and CEO share disposal occurs after news releases, it may be possible that the SEC or investors consider her sales as the informed trading to pursue her own wealth. That is why CEOs are less likely to sell shares after positive news. On the other hand, by the same token, CEOs are more likely sell shares in the open market after negative news releases. It looks suspicious if CEOs dispose shares right before negative news releases from the perspectives of regulators and active investors. To minimize these litigation risks, CEOs would want to sell their shares after negative news releases rather than before negative news releases. The results on CEO stock sales suggest that these sales transactions are not informed and do not play a role of signaling mechanism. Therefore, I will only explore CEO open market purchase side from now on.

Some might argue for the possibility that CEOs purchase shares only for profitability. However, the expected profitability of the open market purchase is one of the important factors that incentivize CEOs to send the signal to the market by trading shares, as share trading is a costly signal without the expected profitability. In addition, it is hard to support this argument because of the short-swing profit rule. The Securities and Exchange Commission (SEC) requires insiders to return any profits realized from open market purchase and sale of their company shares if the transactions occur within a 6-month window, so the regulation discourages insiders' intention to pursue short-term profits. In my data, the average number of days between a purchase date and the next sale date is around 1682 days, which is over 4.5 years. This suggests that my results are not only driven by the profitability story. I address this issue in section 8.

Table 2.2 News Coverage and CEO Trading Patterns

$$\text{LPM: } \Pr(Y = 1 | X_1, X_2, \ldots, X_k) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k$$

This table contains OLS regressions that examine the relation between news coverage and CEO trading pattern. Dependent variable for columns 1 – 6 is CEO share purchase indicator variable, which is equal to 1 if CEO performs open market share purchase. Key independent variable is news coverage variable. LN(News) is natural logarithm of 1 + number of news coverage within a window, which specifies on the top of the table. Control variables include annualized stock returns, natural logarithm of firm size, idiosyncratic volatility, Market-to-Book ratio, The Amihud illiquidity measure, earnings announcement month indicator, dividend record month indicator, institutional ownership, and analyst coverage. In the model, μ_i means each firm's time-invariant specific effect, and ν_t means that year specific effect. X_{it} is a set of explanatory variables, and ε_{it} is an error term, which assumes that $E(\varepsilon_{it})=0$ and $Var(\varepsilon_{it})=\sigma^2$. All models include time and firm fixed effects and cluster standard errors by both firm and year. Brackets contain robust t-statistics and superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

(Continued from the previous page)

	(1) [-2, -1] Buy	(2) [-2, -1] Buy	(3) [-3, -1] Buy	(4) [-3, -1] Buy	(5) [-5, -1] Buy	(6) [-5, -1] Buy
LN(News)	0.001***	0.001***	0.002***	0.001***	0.002***	0.002***
	(6.34)	(5.30)	(6.98)	(5.74)	(7.52)	(6.37)
LN(Size)		-0.001		-0.001		-0.001
		(-1.42)		(-1.51)		(-1.70)
MTB		0.000		0.000		0.000
		(0.66)		(0.73)		(0.88)
Return		-0.010***		-0.010***		-0.010***
		(-4.46)		(-4.47)		(-4.52)
Illiquidity		-0.000		-0.000		-0.000
		(-0.38)		(-0.44)		(-0.56)
IVOL		0.001*		0.001		0.001
		(1.79)		(1.75)		(1.63)
Earnings Month		0.001***		0.001***		0.000***
		(5.54)		(5.39)		(4.97)
Dividend Record Month		0.000**		0.000**		0.000**
		(2.88)		(2.82)		(2.63)
Institutional Ownership		-0.000		-0.000		-0.000
		(-0.57)		(-0.49)		(-0.36)
Analyst Coverage		0.000		0.000		0.000
		(0.41)		(0.35)		(0.17)
Constant	0.002***	0.010	0.001***	0.010*	0.001***	0.011*
	(34.98)	(1.76)	(21.69)	(1.82)	(9.25)	(1.96)
Observations	13,824,801	6,955,190	13,824,801	6,955,190	13,824,801	6,955,190
Adjusted R-squared	0.019	0.026	0.020	0.026	0.020	0.027
Fixed Effect	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year

Table 2.3 Press Release and CEO Trading Patterns

$$\text{LPM: } \Pr(Y = 1 | X_1, X_2, \ldots, X_k) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k$$

This table contains OLS regressions that examine the relation between press release coverage and CEO trading pattern. Dependent variable for columns 1 – 6 is CEO share purchase indicator variable, which is equal to 1 if CEO performs open market share purchase. Key independent variable is press release coverage and news coverage variable. LN(Press) (LN(News)) is natural logarithm of 1 + number of press release coverage (news coverage) within a window, which specifies on the top of the table. Control variables include annualized stock returns, natural logarithm of firm size, idiosyncratic volatility, Market-to-Book ratio, The Amihud illiquidity measure, earnings announcement month indicator, dividend record month indicator, institutional ownership, and analyst coverage. In the model, μ_i means each firm's time-invariant specific effect, and v_t means that year specific effect. X_{it} is a set of explanatory variables, and ε_{it} is an error term, which assumes that $E(\varepsilon_{it})=0$ and $Var(\varepsilon_{it})=\sigma^2$. All models include time and firm fixed effects and cluster standard errors by both firm and year. Brackets contain robust t-statistics and superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

(Continued from the previous page)

	(1) [-2, -1] Buy	(2) [-2, -1] Buy	(3) [-3, -1] Buy	(4) [-3, -1] Buy	(5) [-5, -1] Buy	(6) [-5, -1] Buy
LN(Press)	-0.001***	-0.001***	-0.000***	-0.000***	-0.000	-0.000
	(-3.89)	(-3.80)	(-2.97)	(-3.26)	(-0.75)	(-0.92)
LN(News)	0.001***	0.001***	0.002***	0.002***	0.002***	0.002***
	(6.09)	(5.12)	(6.69)	(5.57)	(7.29)	(6.26)
LN(Size)		-0.001		-0.001		-0.001
		(-1.43)		(-1.51)		(-1.70)
MTB		0.000		0.000		0.000
		(0.58)		(0.62)		(0.78)
Return		-0.010***		-0.010***		-0.010***
		(-4.46)		(-4.47)		(-4.52)
Illiquidity		-0.000		-0.000		-0.000
		(-0.39)		(-0.45)		(-0.56)
IVOL		0.001*		0.001		0.001
		(1.79)		(1.74)		(1.63)
Earnings Month		0.001***		0.001***		0.000***
		(5.50)		(5.34)		(4.86)
Dividend Record Month		0.000**		0.000**		0.000**
		(2.87)		(2.81)		(2.63)
Institutional Ownership		-0.000		-0.000		-0.000
		(-0.56)		(-0.49)		(-0.36)
Analyst Coverage		0.000		0.000		0.000
		(0.42)		(0.36)		(0.18)
Constant	0.002***	0.010	0.001***	0.010*	0.001***	0.011*
	(36.90)	(1.77)	(22.59)	(1.83)	(9.48)	(1.96)
Observations	13,824,801	6,955,190	13,824,801	6,955,190	13,824,801	6,955,190
Adjusted R-squared	0.019	0.026	0.020	0.026	0.020	0.027
Fixed Effect	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year

Table 2.4 News Tone and CEO Trading Patterns

$$\text{LPM: Pr}(\text{Y} = 1 | \text{X}_1, \text{X}_2, \dots, \text{X}_k) = \beta_0 + \beta_1\text{X}_1 + \beta_2\text{X}_2 + \dots + \beta_k\text{X}_k$$

This table contains OLS regressions that examine the relation between new tone and CEO trading pattern. Dependent variable for columns 1 – 6 is CEO share purchase indicator variable, which is equal to 1 if CEO performs open market share purchase. Key independent variables are news coverage variables by news tone. LN(Pos_News) is natural logarithm of 1 + number of positive news coverage, based on composite sentiment score (CSS), within a window, which specifies on the top of the table. LN(Neg_News) is natural logarithm of 1 + number of negative news coverage, based on composite sentiment score (CSS), within a window, which specifies on the top of the table. LN(Neu_News) is natural logarithm of 1 + number of neutral news coverage, based on composite sentiment score (CSS), within a window, which specifies on the top of the table. LN(News) is natural logarithm of 1 + number of news coverage within a window, which specifies on the top of the table. Control variables include annualized stock returns, natural logarithm of firm size, idiosyncratic volatility, Market-to-Book ratio, The Amihud illiquidity measure, earnings announcement month indicator, dividend record month indicator, institutional ownership, and analyst coverage. In the model, μ_i means each firm's time-invariant specific effect, and ν_t means that year specific effect. X_{it} is a set of explanatory variables, and ε_{it} is an error term, which assumes that $E(\varepsilon_{it})=0$ and $Var(\varepsilon_{it})=\sigma^2$. All models include time and firm fixed effects and cluster standard errors by both firm and year. Brackets contain robust t-statistics and superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

(Continued from the previous page)

	(1) [-2, -1] Buy	(2) [-2, -1] Buy	(3) [-3, -1] Buy	(4) [-3, -1] Buy	(5) [-5, -1] Buy	(6) [-5, -1] Buy
LN(Pos_News)	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(5.11)	(4.23)	(5.29)	(4.36)	(5.61)	(4.79)
LN(Neg_News)	0.000***	0.000**	0.000***	0.001***	0.001***	0.001***
	(3.41)	(2.99)	(6.35)	(6.42)	(10.35)	(10.11)
LN(Neu_News)	-0.001***	-0.001***	-0.000***	-0.000**	-0.000	0.000
	(-4.36)	(-3.22)	(-3.20)	(-2.18)	(-1.63)	(0.07)
LN(Size)		-0.001		-0.001		-0.001
		(-1.39)		(-1.46)		(-1.63)
MTB		0.000		0.000		0.000
		(0.51)		(0.55)		(0.63)
Return		-0.010***		-0.010***		-0.010***
		(-4.44)		(-4.45)		(-4.47)
Illiquidity		-0.000		-0.000		-0.000
		(-0.43)		(-0.50)		(-0.66)
IVOL		0.001*		0.001		0.001
		(1.80)		(1.76)		(1.64)
Earnings Month		0.001***		0.000***		0.000***
		(5.49)		(5.31)		(4.84)
Dividend Record Month		0.000**		0.000**		0.000**
		(2.95)		(2.90)		(2.74)
Institutional Ownership		-0.000		-0.000		-0.000
		(-0.54)		(-0.45)		(-0.27)
Analyst Coverage		0.000		0.000		0.000
		(0.40)		(0.32)		(0.13)
Constant	0.002***	0.010	0.002***	0.010*	0.001***	0.011*
	(47.64)	(1.73)	(30.53)	(1.79)	(15.12)	(1.92)
Observations	13,824,801	6,955,190	13,824,801	6,955,190	13,824,801	6,955,190
Adjusted R-squared	0.020	0.026	0.020	0.027	0.020	0.027
Fixed Effect	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year

2.4.2 The Information Environment

To provide further evidence that the CEO responds to the media differently, I conduct analyses conditional on the firms' information environment. Lakonishok and Lee (2001) find that insiders' trades are informative for small firms. This suggests that the firms' information environment could be an important factor that constructs the informativeness of the transactions. I expect that the news will spread out in a big way when the firms' information environment is more intensive if the news tone is informative to investors. Thus, investors will have better access to the public information and have more channels for receiving the public information. This could mitigate concerns about the market underreaction and overreaction, as an intensive information environment results in more efficient news dissemination.

To identify the transparent information environment, I first use the natural logarithm of analyst coverage over the previous 12 months. The number of analysts that follow a company reduces information asymmetry between insiders and outside investors. Analysts can disseminate firm-specific news more efficiently to the market. Due to this reason, firms with intensive analyst following are less likely to be mispriced after news releases. Thus, CEOs would not need to send the signal to the market for the purpose of correcting the released information. Using analyst coverage, I classify firms as having a highly intensive information environment if the analyst coverage of the firm falls into the top quintile of the sample distribution, and as less intensive otherwise.

I also define the highly transparent information environment based on investors' information acquisition activities through the SEC EDGAR system in the same way. I assume that the more investors search on a firm via the SEC EDGAR system, the more information about the firm that investors acquire. The Division of Economic and Risk

Analysis of the SEC provides the investor search data on its website.[5] I use Python code to collect the search data from the SEC EDGAR server log files. The data contains the IP addresses that searched any SEC filings via the EDGAR system, the time the IPs search on filings, CIK identifiers, a SEC document accession number associated with the document requested, an indicator variable, which is equal to one if an IP is considered as a web crawler, log file status whether the request was successfully granted or was failed, and so on. I merge the SEC EDGAR search data with my main dataset using the CIK code. I have smaller sample size after matching the data because of shorter sample period of the SEC EDGAR data, which is from 2003 to 2016. To mitigate concerns about massive searches by web crawlers and double counting issue, I exclude searches that are indicated as web crawling, failed search requests, search requests on index page, and IP addresses that search over 50 unique firms within a day.

To identify the active information acquisition, I construct cumulative number of search volume variable over the previous 12 months. Then, I classify firms as having an active information acquisition if the cumulative search volume of the firm falls into the top quintile of the sample distribution, and as less active otherwise. I estimate linear probability models, including interaction terms between the news tone and information environment indicator variable, and report the results in Table 5.

As evidenced from Panel A of Table 5, the coefficients on the interaction terms between intensive analyst coverage and positive news coverage and between intensive analyst coverage and negative news coverage are negative and statistically significant. The results show that, compared with CEOs in firms with less intensive analyst coverage, CEOs in firms with highly intensive analyst coverage are less likely to purchase their

---

[5] The SEC website (https://www.sec.gov/dera/data/edgar-log-file-data-set.html) provides detailed description about the data as well as log files.

firms' shares as positive (negative) news coverage increases. This could be because of less likelihood of mispricing after news release. With a transparent information environment, CEOs may not have any additional information about the firm-specific news release that the market has not yet recognized. The results suggest that CEOs may not have to communicate with their investors by trading their shares under the transparent information environment because of effective information dissemination. These are consistent with my expectation above.

In Panel B of Table 5, I report the results for examining the relationship between news tone and CEO trading pattern conditional on information environment, proxied by the SEC EDGAR searches by investors. The results are consistent with the findings using analyst coverage as the proxy for information environment. CEOs are less likely to purchase shares after news releases regardless of news tone if their investors are active to collect firm-specific information through the SEC EDGAR system. The results suggest that CEOs do not need to make the news salient if their investors actively acquire the relevant information.

Table 2.5 News Tone and CEO Trading Patterns conditional on Information Environment

$$\text{LPM: Pr}(Y = 1 | X_1, X_2, \ldots, X_k) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k$$

This table contains OLS regressions that examine the relation between new tone and CEO trading pattern conditional on information environment. To identify firms with good information environment, I use intensive analyst coverage. Dependent variable for columns 1 – 6 is CEO share purchase indicator variable, which is equal to 1 if CEO performs open market share purchase. Key independent variables are news coverage variables by news tone. LN(Pos_News) is natural logarithm of 1 + number of positive news coverage, based on composite sentiment score (CSS), within a window, which specifies on the top of the table. LN(Neg_News) is natural logarithm of 1 + number of negative news coverage, based on composite sentiment score (CSS), within a window, which specifies on the top of the table. LN(Neu_News) is natural logarithm of 1 + number of neutral news coverage, based on composite sentiment score (CSS), within a window, which specifies on the top of the table. LN(News) is natural logarithm of 1 + number of news coverage within a window, which specifies on the top of the table. Control variables include annualized stock returns, natural logarithm of firm size, idiosyncratic volatility, Market-to-Book ratio, The Amihud illiquidity measure, earnings announcement month indicator, dividend record month indicator, institutional ownership, and analyst coverage. In the model, μ_i means each firm's time-invariant specific effect, and v_t means that year specific effect. X_{it} is a set of explanatory variables, and ε_{it} is an error term, which assumes that $E(\varepsilon_{it})=0$ and $Var(\varepsilon_{it})=\sigma^2$. All models include time and firm fixed effects and cluster standard errors by both firm and year. Brackets contain robust t-statistics and superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

(Continued from the previous page)

Panel A: Intensive Analyst Coverage

	(1) [-2, -1] Buy	(2) [-2, -1] Buy	(3) [-3, -1] Buy	(4) [-3, -1] Buy	(5) [-5, -1] Buy	(6) [-5, -1] Buy
Transparent X LN(Pos_News)	-0.002***	-0.004***	-0.002***	-0.004***	-0.002***	-0.004***
	(-3.77)	(-4.93)	(-3.93)	(-5.09)	(-4.11)	(-5.50)
Transparent X LN(Neg_News)	-0.000	0.000	-0.000**	-0.000	-0.001***	-0.001***
	(-0.11)	(1.09)	(-2.16)	(-1.40)	(-4.22)	(-4.92)
LN(Pos_News)	0.004***	0.005***	0.004***	0.005***	0.004***	0.005***
	(5.01)	(4.68)	(5.24)	(4.82)	(5.61)	(5.24)
LN(Neg_News)	0.000**	0.000	0.001***	0.001***	0.001***	0.001***
	(2.22)	(1.64)	(5.54)	(5.51)	(8.68)	(8.73)
LN(Neu_News)	-0.001***	-0.000***	-0.000***	-0.000*	-0.000	0.000
	(-4.29)	(-3.02)	(-3.09)	(-1.93)	(-1.52)	(0.23)
Transparent	0.000*	0.000	0.000**	0.000*	0.000***	0.001***
	(1.78)	(1.34)	(2.57)	(2.15)	(3.88)	(3.52)
Constant	0.002***	0.009	0.001***	0.010	0.001***	0.010
	(34.27)	(1.61)	(24.72)	(1.64)	(12.26)	(1.73)
Observations	13,824,801	6,955,190	13,824,801	6,955,190	13,824,801	6,955,190
Adjusted R-squared	0.020	0.027	0.020	0.027	0.020	0.027
Control Variables	No	Yes	No	Yes	No	Yes
Fixed Effect	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year

(Continued from the previous page)

Panel B: Active Information Acquisition

	(1)	(2)	(3)	(4)	(5)	(6)
	[-2, -1]	[-2, -1]	[-3, -1]	[-3, -1]	[-5, -1]	[-5, -1]
	Buy	Buy	Buy	Buy	Buy	Buy
Active Information Acquisition X LN(Pos_News)	-0.003***	-0.003***	-0.003***	-0.003***	-0.002***	-0.002***
	(-6.73)	(-6.00)	(-7.00)	(-6.45)	(-6.67)	(-6.21)
Active Information Acquisition X LN(Neg_News)	0.000	0.000	-0.000	0.000	-0.000**	-0.000**
	(0.69)	(1.55)	(-1.11)	(0.10)	(-2.50)	(-2.21)
LN(Pos_News)	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
	(14.29)	(10.66)	(15.02)	(11.20)	(16.07)	(11.88)
LN(Neg_News)	0.000	0.000	0.001***	0.001***	0.001***	0.001***
	(1.07)	(0.31)	(4.52)	(3.16)	(8.94)	(7.91)
LN(Neu_News)	-0.001***	-0.001***	-0.000***	-0.000***	-0.000***	-0.000
	(-7.06)	(-4.27)	(-5.02)	(-2.71)	(-2.62)	(-0.28)
Active Information Acquisition	0.000**	0.000**	0.000***	0.001***	0.001***	0.001***
	(2.18)	(2.26)	(2.79)	(2.70)	(3.68)	(3.37)
Constant	0.001***	0.009	0.001***	0.009*	0.001***	0.010*
	(7.44)	(1.59)	(6.97)	(1.65)	(6.06)	(1.82)
Observations	11,194,064	6,571,281	11,194,064	6,571,281	11,194,064	6,571,281
Adjusted R-squared	0.027	0.028	0.027	0.028	0.028	0.028
Fixed Effect	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year

2.4.3 Institutional Investors

In this section, I examine whether intensive institutional ownership and types of institutional investors are related to CEO trading patterns after news releases.

In Panel A of Table 6, using institutional ownership at the previous quarter end, I classify firms as having a highly intensive institutional ownership if the institutional ownership of the firm falls into the top quintile of the sample distribution, and as less intensive otherwise. High institutional ownership is related to active firm-specific information gathering and better governance mechanism because certain types of institutional investors are more active to collect the information and to monitor CEOs. Thus, I expect that CEOs in firms with high institutional ownership may have stronger incentives to send the signal to the market if negative news releases and weaker incentives to communicate with the market if positive news releases. Because downside risk is more severe in the case of the market overreaction to their negative news than in the case of the market underreaction to their positive news, CEOs have career and reputation concerns under the oversight of institutional institutions who occupy high portion of their firms.

Consistent with the expectation above, Panel A of Table 6 shows that CEOs in firms with high institutional ownership are less likely to purchase shares after positive news releases and are more likely to purchase shares after negative news releases. The results suggest that CEOs under the intensive institutional monitoring have stronger incentives to correct the mispricing in the case of the market overreaction to the negative news because of career and reputation concerns. In this table, I only look at aggregate institutional ownership, so, next step is to disentangle the institutional ownership into three different groups according to key characteristics of institutional investors.

Based on Bushee (2001), I classify institutional investors into three groups, such as dedicated, quasi-indexer, and transient, in terms of their particular characteristics and investment patterns. I classify firms into quintile based on the portion of dedicated, transient, and quasi-indexer ownership. Firms in the top quintile of such ownership are identified as firms with high dedicated (transient, quasi-indexer) ownership.

Transient institutions may not directly affect CEO incentives to communicate with the market, but they could indirectly affect CEO incentives because they can sell their shares when mispricing occurs, and it negatively affects their portfolios. Similar to transient institutions, quasi-indexers may not affect CEO incentives directly, but they would technically dispose their shares if the firm underperforms their peers or a certain index. It indirectly motivates CEOs to send the signal to the market to correct the information by making the news salient through their trading patterns. On the other hand, Dedicated institutions would play an important role in monitoring CEOs. I expect that CEOs in firms with high dedicated, transient, and quasi-indexer ownership have stronger incentives to communicate with their investors after negative news releases.

The results are reported in Panel B of Table 6. I see the relation is statistically and economically stronger for the firms with high dedicated, transient, and quasi-indexer institutional investor ownership that have potentially more intensive monitoring function. The results are consistent with the previous results with the portion of total institutional ownership to market capitalization of the company.

Table 2.6 News Tone and CEO Trading Patterns conditional on Institutional Ownership

$$\text{LPM}: \Pr(Y = 1 | X_1, X_2, \dots, X_k) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k$$

This table contains OLS regressions that examine the relation between new tone and CEO trading pattern conditional on institutional ownership. To identify firms with high institutional ownership, I use institutional ownership normalized by shares outstanding. Firms that fall into the third quartile are considered as firms with high institutional ownership. Dependent variable for columns 1 – 6 is CEO share purchase indicator variable, which is equal to 1 if CEO performs open market share purchase. Key independent variables are news coverage variables by news tone. LN(Pos_News) is natural logarithm of 1 + number of positive news coverage, based on composite sentiment score (CSS), within a window, which specifies on the top of the table. LN(Neg_News) is natural logarithm of 1 + number of negative news coverage, based on composite sentiment score (CSS), within a window, which specifies on the top of the table. LN(Neu_News) is natural logarithm of 1 + number of neutral news coverage, based on composite sentiment score (CSS), within a window, which specifies on the top of the table. LN(News) is natural logarithm of 1 + number of news coverage within a window, which specifies on the top of the table. Control variables include annualized stock returns, natural logarithm of firm size, idiosyncratic volatility, Market-to-Book ratio, The Amihud illiquidity measure, earnings announcement month indicator, dividend record month indicator, institutional ownership, and analyst coverage. In the model, μ_i means each firm's time-invariant specific effect, and v_t means that year specific effect. X_{it} is a set of explanatory variables, and ε_{it} is an error term, which assumes that $E(\varepsilon_{it})=0$ and $Var(\varepsilon_{it})=\sigma^2$. All models include time and firm fixed effects and cluster standard errors by both firm and year. Brackets contain robust t-statistics and superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

(Continued from the previous page)

Panel A: High Institutional Ownership

	(1) [-2, -1] Buy	(2) [-2, -1] Buy	(3) [-3, -1] Buy	(4) [-3, -1] Buy	(5) [-5, -1] Buy	(6) [-5, -1] Buy
High Ownership X LN(Pos_News)	-0.002***	-0.002***	-0.002***	-0.003***	-0.002***	-0.003***
	(-3.36)	(-4.88)	(-3.21)	(-4.90)	(-3.37)	(-4.89)
High Ownership X LN(Neg_News)	0.001**	0.001**	0.001*	0.001**	0.000	0.000
	(2.43)	(2.90)	(2.00)	(2.38)	(1.72)	(1.65)
LN(Pos_News)	0.004***	0.004***	0.004***	0.004***	0.005***	0.004***
	(4.69)	(4.43)	(4.74)	(4.52)	(5.09)	(4.85)
LN(Neg_News)	-0.000	-0.000	0.000	0.000*	0.001***	0.001***
	(-0.83)	(-0.11)	(0.66)	(2.03)	(3.87)	(6.12)
LN(Neu_News)	-0.001***	-0.000***	-0.000***	-0.000*	-0.000	0.000
	(-4.42)	(-3.24)	(-3.23)	(-2.13)	(-1.57)	(0.31)
High Ownership	-0.000	-0.000	0.000	0.000	0.000*	0.000
	(-0.06)	(-0.16)	(0.61)	(0.51)	(1.84)	(1.66)
Constant	0.002***	0.010	0.002***	0.010	0.001***	0.011*
	(33.41)	(1.71)	(24.72)	(1.76)	(12.06)	(1.89)
Observations	13,824,801	6,955,190	13,824,801	6,955,190	13,824,801	6,955,190
Adjusted R-squared	0.020	0.026	0.020	0.027	0.020	0.027
Control Variables	No	Yes	No	Yes	No	Yes
Fixed Effect	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year

(Continued from the previous page)

Panel B: Institutional Ownership Classification

	(1) [-2, -1]	(2) [-3, -1] Dedicated	(3) [-5, -1]	(4) [-2, -1]	(5) [-3, -1] Transient	(6) [-5, -1]	(7) [-2, -1]	(8) [-3, -1] Quasi-Indexer	(9) [-5, -1]
D(Classification) X LN(Pos_News)	-0.002***	-0.002***	-0.002***	-0.001**	-0.001**	-0.001**	-0.002***	-0.002***	-0.002***
	(-4.81)	(-4.79)	(-4.85)	(-2.06)	(-2.17)	(-2.51)	(-4.40)	(-4.54)	(-4.84)
D(Classification) X LN(Neg_News)	0.000**	0.000**	0.000*	0.001***	0.000**	0.000	0.001***	0.001***	0.000
	(2.58)	(2.08)	(1.65)	(2.69)	(2.18)	(1.58)	(3.64)	(2.65)	(1.56)
LN(Pos_News)	0.004***	0.004***	0.004***	0.003***	0.003***	0.003***	0.003***	0.004***	0.004***
	(7.51)	(7.84)	(8.72)	(7.65)	(8.20)	(9.10)	(7.46)	(7.87)	(8.77)
LN(Neg_News)	0.000	0.000***	0.001***	0.000	0.000***	0.001***	0.000	0.000***	0.001***
	(1.33)	(3.73)	(8.01)	(1.18)	(3.78)	(7.93)	(0.24)	(2.65)	(6.53)
LN(Neu_News)	-0.001***	-0.000**	-0.000	-0.001***	-0.000**	0.000	-0.000***	-0.000**	0.000
	(-4.06)	(-2.47)	(-0.04)	(-4.01)	(-2.38)	(0.16)	(-4.00)	(-2.33)	(0.29)
D(Classification)	0.000	0.000	0.000*	0.000***	0.000***	0.000***	0.000**	0.000***	0.001***
	(0.43)	(1.09)	(1.87)	(3.22)	(3.67)	(4.53)	(2.39)	(3.27)	(4.61)
Constant	0.011**	0.011**	0.012**	0.011**	0.011**	0.012**	0.011**	0.011**	0.012**
	(2.06)	(2.13)	(2.32)	(2.12)	(2.20)	(2.41)	(2.10)	(2.19)	(2.40)
Observations	6,930,403	6,930,403	6,930,403	6,930,403	6,930,403	6,930,403	6,930,403	6,930,403	6,930,403
Adjusted R-squared	0.026	0.027	0.027	0.026	0.027	0.027	0.026	0.027	0.027
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year

2.4.4 The News Category

In this section, I examine whether the news category is associated with CEO trading patterns after news releases. Based on the RavenPack News Analytics category, I define news about revenue, earnings, analyst rating, and credit rating as hard news, while other topics are considered soft news. Hard news captures firms' fundamentals, while soft news comprises less value-relevant news.

Hard news is more likely to contain numerical information that can provide direct information about firm value. For example, news about earnings provides numeric data about firms' current earnings and previous earnings. Investors can compare the current value with the previous value easily, even if they do not have enough financial knowledge to interpret it or pay limited attention to the news story. However, investors cannot clearly analyze the effect of news about mergers and acquisitions if they are not familiar with industry-specific information, such as the target value, firm value of possible alternative target firms, and so on. Thus, there will be sufficient investor attention to hard news and limited attention to soft news.

Table 7 shows two different patterns depending on the news category. First, the CEO trading patterns following hard news coverage are similar to the CEO trading patterns in firms with transparent information environments, suggesting that hard news is more visible because it contains information about firms' fundamentals. Investors pay more attention to the hard news and they would not need to know additional information about the hard news to interpret the news correctly, so CEOs only need to mitigate the concerns about the market's overreaction to negative hard news. Second, the CEO trading patterns following soft news coverage show that CEOs only need to confirm positive soft news when the market underreacts to it. Because soft news is not related to firms' fundamentals, investors may pay limited attention to the soft news or need additional knowledge to interpret the news. In addition, outside investors may not have enough time to analyze the information on time. It is plausible that even analysts and institutional investors could overlook the soft news because of its opaqueness. Thus, CEOs have incentives to send signals to the market in the case of market underreaction. CEOs do not have to care about the market's underreaction to negative soft news because it is beneficial to their shareholder wealth, even though the market has incomplete information.

Among trading patterns in Table 7, the most unique trading pattern is the trading pattern on negative hard news. Different from positive soft news, there might be much less concern about CEO's intention of trades. To be specific, some may interpret results of Table 7 that CEOs perform informed trades on positive soft news to pursue their personal wealth, while I interpret the result that CEOs have incentives to correct the mispricing by purchasing shares in the open market after the positive soft news releases. Open market purchase after negative hard news is difficult to interpret as only profitability story. The result suggests that CEOs have incentives to purchase more shares as negative hard news releases to correct the market overreaction to the negative hard news.

Table 2.7 Relation between News Tone and CEO Trading Patterns by News Category

$$\text{LPM}: \Pr(Y = 1 | X_1, X_2, \ldots, X_k) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k$$

This table contains OLS regressions that examine the relation between new tone and CEO trading pattern by news category. Based on RavenPack News Analytics category, I define news about revenue, earnings, analyst rating, and credit rating as hard news, and the other topics are considered as soft news. Hard news would capture firms' fundamentals. On the other hand, soft news would be less value-relevant news. Dependent variable for columns 1 – 6 is CEO share purchase indicator variable, which is equal to 1 if CEO performs open market share purchase. Dependent variable for the other columns is CEO share sales indicator variable, which is equal to 1 if CEO performs open market share sales. Key independent variables are news coverage variables by news categories. LN(Hard (Soft)_News) is natural logarithm of 1 + number of hard (soft) news coverage within a window, which specifies on the top of the table. LN(Hard (Soft)_Pos) is natural logarithm of 1 + number of positive hard (soft) news coverage, based on composite sentiment score (CSS), within the window. LN(Hard (Soft)_Neg) is natural logarithm of 1 + number of negative hard (soft) news coverage, based on composite sentiment score (CSS), within the window. LN(Hard (Soft)_Neu) is natural logarithm of 1 + number of neutral hard (soft) news coverage, based on composite sentiment score (CSS), within the window. LN(News) is natural logarithm of 1 + number of news coverage within the window. Control variables include annualized stock returns, natural logarithm of firm size, idiosyncratic volatility, Market-to-Book ratio, The Amihud illiquidity measure, earnings announcement month indicator, dividend record month indicator, institutional ownership, and analyst coverage. In the model, μ_i means each firm's time-invariant specific effect, and v_t means that year specific effect. X_{it} is a set of explanatory variables, and ε_{it} is an error term, which assumes that E(ε_{it})=0 and Var(ε_{it})=σ^2. All models include time and firm fixed effects and cluster standard errors by both firm and year. Brackets contain robust t-statistics and superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

(Continued from the previous page)

	(1) [-2, -1] Buy	(2) [-3, -1] Buy	(3) [-5, -1] Buy	(4) [-2, -1] Buy	(5) [-3, -1] Buy	(6) [-5, -1] Buy
LN(Hard_News)	0.000**	0.001***	0.001***			
	(2.36)	(6.92)	(9.53)			
LN(Soft_News)	0.002***	0.002***	0.002***			
	(4.64)	(4.88)	(5.29)			
LN(Hard_Pos)				-0.000**	-0.000*	-0.000
				(-2.45)	(-2.03)	(-1.36)
LN(Hard_Neg)				0.001***	0.002***	0.003***
				(5.25)	(6.65)	(8.48)
LN(Hard_Neu)				-0.000**	-0.000	0.000***
				(-2.35)	(-0.10)	(3.43)
LN(Soft_Pos)				0.004***	0.004***	0.004***
				(3.73)	(3.77)	(4.08)
LN(Soft_Neg)				0.000	0.000	0.000**
				(1.57)	(1.76)	(2.18)
LN(Soft_Neu)				-0.000*	-0.000	0.000
				(-2.04)	(-1.27)	(0.54)
Observations	6,955,190	6,955,190	6,955,190	6,955,190	6,955,190	6,955,190
Adjusted R-squared	0.026	0.026	0.027	0.026	0.027	0.027
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year

2.4.5 The Market's Reaction to CEO Trading Patterns

Do CEO trading patterns have credibility? This is an important empirical question because investors can learn from CEO trading pattern if CEOs purchase shares in the open market to communicate with their investors and investors perceive that the additional information provided by CEO trading patterns is credible. CEOs cannot communicate with the investors if they ignore the signals from CEOs. Thus, in this section, I investigate the market reaction to CEO open market purchases. I estimate cumulative abnormal returns (CAR) for various time windows to capture the market reaction to the CEO trading pattern. I collect stock returns from the CRSP and conduct an event study using Eventus. I use both a market model and a constant mean return model with a 255-day estimation period ending 46 days prior to the announcement date.

Table 8 shows ordinary least squares (OLS) regressions of the CAR on news variables and firm-level control variables. For this analysis, I only include CEO open market purchases. All control variables are measured at the end of the prior fiscal year. All regressions include firm and year fixed effects. I correct all standard errors for heteroskedasticity and group correlation at the firm level.

Columns 1–3 of Panel A in Table 8 show that the market positively reacts to CEO open market purchases, which are related to news releases, among all the open market purchases. This shows that CEO's post-news purchase transactions are more informative than purchase transactions in other periods, and the market learns from the CEO trading patterns. Regardless of news releases, CEO purchases always correct mispricing in the market. CEO purchases following news make the news salient. This is why the market reacts positively to CEO purchases in the short run.

In Columns 4–6 of Panel A in Table 8, I find a positive market reaction to CEOs' open market purchases, related to positive news coverage in the pre-transaction period, but the positive market reaction disappears in CEOs' open market purchases based on the [–5, –1] window. This suggests that such CEO trading patterns would have significant credibility, but CEOs tend to react to the market underreaction immediately because they have additional positive information, which means that the cost of trading is relatively small. In contrast, I find a positive market reaction to negative news-related CEO purchases, and this result only holds for the [–5, –1] window specification. This suggests that CEOs tend to send the signal through their trading patterns carefully in the case of market overreaction because of the relatively high cost of trading.

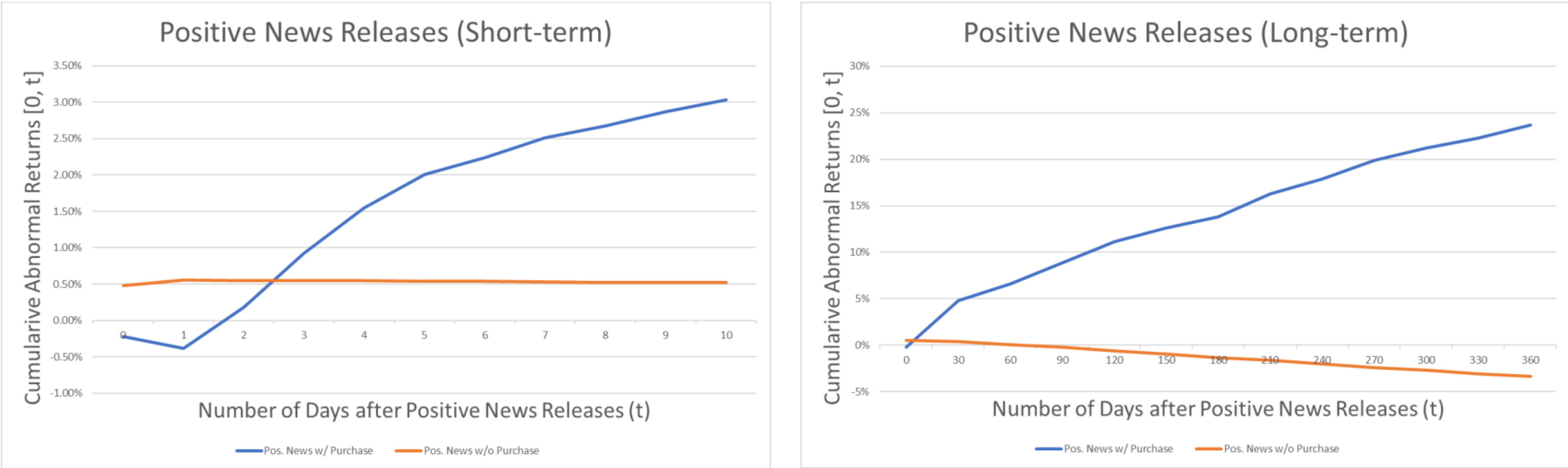
Panel B in Table 8 illustrates the long-run market reaction to CEO open market purchases. Panel A of Table 8 suggests that CEO open market purchases after news releases are more profitable than purchases in other periods. However, it only shows the short-run market reaction. Because the short-run market reaction is related to both news releases and CEO purchases, it is important to check the long-run market reaction. I expect that the market will respond promptly to the additional information through the CEO trading patterns; moreover, the news-related purchases will not outperform in the long-run because CEOs have intentions to correct the information by purchasing shares during the periods and profitability is not the only reason why they trade the shares.

The long-run market reaction analysis shows that the news-related purchases perform better only in the short run. This is consistent with the expectation I outlined above and suggests that profitability is not the only motivation for the CEO trading pattern after news releases.

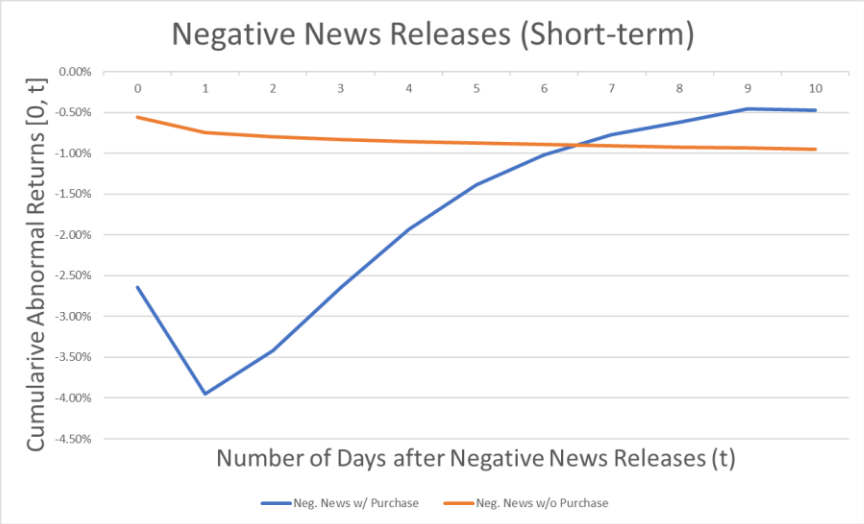
Figure 2.3 Market Reactions to News Releases

These figures show the market reactions to news releases based on cumulative abnormal returns (CAR). In each figure, I compare news releases, followed by CEO open market purchase, with the other news releases. In Panel A, I investigate market reactions to positive news releases, and Panel B shows market reactions to negative news releases. Each panel include both short-term market reaction and long-term market reaction to news releases. Number of days is computed based on business days.

Panel A. Market Reactions to Positive News Releases



Panel B. Market Reactions to Negative News Releases



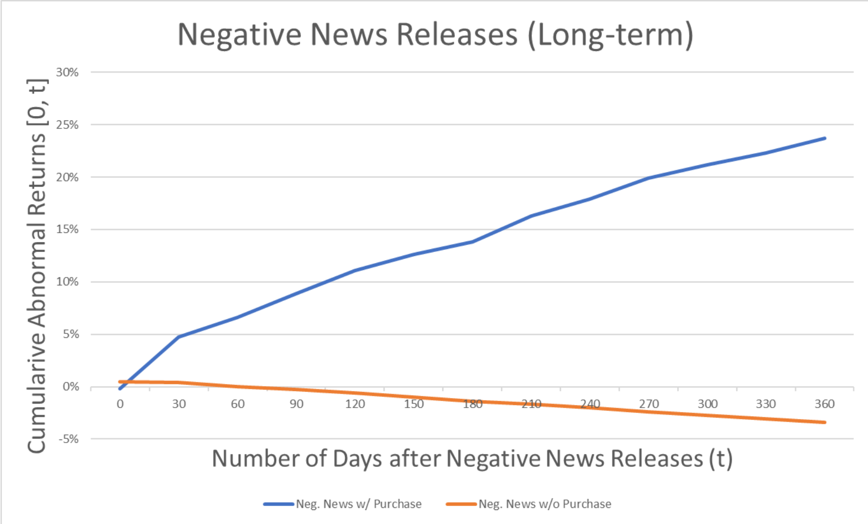


Table 2.8 Market Reaction to CEO Purchases around News Releases

$$\text{OLS: } \mathrm{Y_{it}} = \beta_0 + \beta_1 \mathrm{X_1} + \beta_2 \mathrm{X_2} + \cdots + \beta_k \mathrm{X_k} + \mu_i + \nu_t + \varepsilon_{it}$$

Table 8 shows results of OLS regressions of cumulative abnormal returns from days 0 to +1 around CEO open market purchase on News variables and control variables. Key independent variables are news coverage variables by news tone. LN(Pos_News) is natural logarithm of 1 + number of positive news coverage, based on composite sentiment score (CSS), within a window, which specifies on the top of the table. LN(Neg_News) is natural logarithm of 1 + number of negative news coverage, based on composite sentiment score (CSS), within a window, which specifies on the top of the table. LN(Neu_News) is natural logarithm of 1 + number of neutral news coverage, based on composite sentiment score (CSS), within a window, which specifies on the top of the table. LN(News) is natural logarithm of 1 + number of news coverage within a window, which specifies on the top of the table. Control variables include annualized stock returns, natural logarithm of firm size, idiosyncratic volatility, Market-to-Book ratio, The Amihud illiquidity measure, earnings announcement month indicator, dividend record month indicator, institutional ownership, and analyst coverage. In the model, μ_i means each firm's time-invariant specific effect, and ν_t means that year specific effect. X_{it} is a set of explanatory variables, and ε_{it} is an error term, which assumes that $E(\varepsilon_{it})=0$ and $Var(\varepsilon_{it})=\sigma^2$. All models include time and firm fixed effects and cluster standard errors by both firm and year. Brackets contain robust t-statistics and superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Panel A: Short-run Market Reaction

	(1) [-2, -1] CAR[0, 2] Market Model	(2) [-3, -1] CAR[0, 2] Market Model	(3) [-5, -1] CAR[0, 2] Market Model
News-related Buy	0.004**	0.005***	0.005***
	(2.17)	(3.11)	(3.40)
LN(Size)	-0.022***	-0.022***	-0.022***
	(-7.77)	(-7.79)	(-7.80)
MTB	-0.002**	-0.002**	-0.002**
	(-2.01)	(-2.01)	(-1.98)
Illiquidity	0.003	0.003	0.002
	(0.86)	(0.85)	(0.84)
IVOL	0.011**	0.011**	0.011**
	(2.15)	(2.16)	(2.16)
Constant	0.261***	0.262***	0.263***
	(7.64)	(7.65)	(7.66)
Observations	20,692	20,692	20,692
Adjusted R-squared	0.129	0.129	0.129
Control Variables	Yes	Yes	Yes
Fixed Effect	Firm & Year	Firm & Year	Firm & Year

(Continued from the previous page)

Panel B: Long-run Market Reaction

	(1) CAR[0, 30] Market Model	(2) CAR[0, 60] Market Model	(3) CAR[0, 90] Market Model	(4) CAR[0, 120] Market Model	(5) CAR[0, 150] Market Model	(6) CAR[0, 180] Market Model	(7) CAR[0, 210] Market Model	(8) CAR[0, 240] Market Model
News-related Buy	0.012***	0.010**	0.018***	0.022***	0.024***	0.022***	0.029***	0.028***
	(3.21)	(2.10)	(3.19)	(3.27)	(3.19)	(2.62)	(2.98)	(2.87)
LN(Size)	-0.114***	-0.186***	-0.260***	-0.334***	-0.398***	-0.462***	-0.529***	-0.580***
	(-11.37)	(-11.59)	(-12.75)	(-12.87)	(-13.40)	(-13.74)	(-14.34)	(-15.03)
MTB	-0.011***	-0.015***	-0.018***	-0.021**	-0.028**	-0.036***	-0.043***	-0.047***
	(-3.50)	(-3.10)	(-2.87)	(-2.21)	(-2.33)	(-2.60)	(-2.65)	(-2.69)
Illiquidity	0.006	0.013	0.019	0.030	0.044**	0.062***	0.070***	0.072***
	(0.59)	(1.07)	(1.21)	(1.57)	(2.28)	(2.91)	(2.95)	(2.89)
IVOL	0.032**	0.037*	0.079***	0.112***	0.119***	0.140***	0.142***	0.137***
	(2.04)	(1.75)	(3.07)	(3.46)	(3.60)	(3.77)	(3.49)	(3.09)
Constant	1.384***	2.285***	3.142***	4.032***	4.803***	5.608***	6.431***	7.129***
	(10.99)	(11.63)	(12.17)	(12.59)	(13.71)	(14.24)	(15.18)	(16.16)
Observations	24,332	24,332	24,332	24,332	24,329	24,328	24,328	24,328
Adjusted R-squared	0.293	0.364	0.412	0.445	0.470	0.495	0.510	0.518
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year

2.4.6 Do CEOs Intend to Communicate with the Market?

In previous sections, I have found that CEOs are more likely to purchase shares after news releases and these trading patterns vary depending on the news tone, firms' information environments, and news categories. I interpret the results as showing that CEOs have incentives to correct the market's misperception about the revealed information by purchasing shares in the open market.

A possible alternative explanation for the empirical results, however, is that CEOs pursue their profitability by exploiting private information. If CEOs have unrevealed positive information and they want to exploit it for their own wealth, then they may want to purchase shares when the market underreacts to the revealed positive news or overreacts to the revealed negative news to pursue short-term profits.

To support the alternative story, CEOs should realize positive profits after their open market purchases. This means that they have to sell the shares at a premium. Based on the short-swing profit rule, corporate insiders must return any profits through open market transactions of their firm's stock if the insiders sell the shares within 6 months after the purchase. Thus, CEOs may sell shares around 180 days after the open market purchase if they are trading only for profitability. In contrast, CEOs may not care about timing of the first sale transaction if they have intentions to communicate with the market. Panel A of Table 9 shows that average number of days between the open market purchase and the next share disposal in the open market is above 4 years, which significantly exceeds the 180 days. This suggests that profitability is not the only reason for CEOs to trade their shares in the open market.

The literature on option backdating shows that there would be significant reporting gaps if insiders exploited the private information to increase their personal wealth (e.g., Lie 2005; Heron and Lie 2007). In contrast, CEOs would have incentives to report their transactions as early as possible if they have intentions to communicate with the market. Because CEOs want to send the signal to correct the market's misperception about the news in this case, they do not have any incentives to delay the reporting. Thus, I hypothesize that the reporting gaps will be smaller for open market purchases following news releases.

Thomson Reuters Insider Filing data provide both the transaction date and reporting date. Following previous studies (e.g., Lie 2005; Heron and Lie 2007), I define the reporting gaps as the number of days between the transaction date and reporting date.

In the pre-SOX period, the SEC requires insiders to report their transactions to the SEC within 10 days following the last day of the calendar month in which the transaction occurs. Thus, the maximum reporting gap should be around 40 days. I eliminate all pre-SOX observations with reporting gaps exceeding 40 days. In the post-SOX period, the SEC requires 2 days to report transactions, so the reporting gaps during the post-SOX period should be shorter than 2 days. However, there are reporting gap observations, exceeding 2 days, even after the implementation of the SOX. To be conservative, I drop all observations that have longer reporting gaps than 2 days in the post-SOX period.

In Panel B of Table 9, I regress the reporting gap on news variables and control variables. Columns 1–3 show that the reporting gaps decrease as the cumulative number of news before the open market purchase increases, regardless of the time windows. This is consistent with the hypothesis that CEOs would report more quickly if they intend to correct the market underreaction to the released positive news or overreaction to the released negative news. Columns 4–6 provide empirical evidence that the reverse relation between reporting gaps and cumulative number of news in the pre-transaction periods are robust, even after controlling for time-varying firm characteristics, stock market controls, time-invariant firm characteristics, and time trends.

The empirical evidence in this section highlights that pursuing profitability is not the only reason why CEOs trade their shares in the open market. While I cannot completely rule out the profitability explanation, it appears that CEOs intend to communicate with their investors.

Table 2.8 Do CEOs have intentions to communicate with the market?

Table 9 provides empirical evidence that CEOs have intentions to communicate with the market. Panel A of Table 9 shows average number of days between CEO open-market purchase and her following sale transaction. If there is no subsequent sale transaction after the purchase, then I use the last available date of a firm in my sample to calculate the number of days between the purchase and the subsequent sale. News-related open market purchase is a purchase transaction after news releases. I use [-5, -1] window to construct this variable. All other purchases are classified as Other open market purchase. Panel B of Table 9 shows results of OLS regressions of CEO purchase reporting gaps on news variables and control variables. Key dependent variable, Reporting Gap, is natural log of (1 + number of days between CEO open market purchase transaction date (trandate) and CEO report date to the SEC (secdate)). If there are multiple purchase transactions within a day, then I consider the shortest reporting gap as the reporting gap for the day. Key independent variable is news coverage variable. LN(News) is natural logarithm of 1 + number of news coverage within a window, which specifies on the top of the table. Control variables include annualized stock returns, natural logarithm of firm size, idiosyncratic volatility, Market-to-Book ratio, The Amihud illiquidity measure, earnings announcement month indicator, dividend record month indicator, institutional ownership, and analyst coverage. In the model, μ_i means each firm's time-invariant specific effect, and v_t means that year specific effect. X_{it} is a set of explanatory variables, and ε_{it} is an error term, which assumes that $E(\varepsilon_{it})=0$ and $Var(\varepsilon_{it})=\sigma^2$. All models include time and firm fixed effects and cluster standard errors by both firm and year. Brackets contain robust t-statistics and superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Panel A: Average Number of Days between Purchase and First Sale following the Purchase

	N	Average number of days between a purchase date and the next sales date
All open-market purchase	27,595	1681.679 days (4.61 years)
News-related open-market purchase	13,860	1418.464 days (3.89 years)
Other open-market purchase	13,735	1947.289 days (5.34 years)

(Continued from the previous page)

Panel B: Relation between Reporting Gap and Pre-Purchase News Coverage

	(1) [-2, -1] Reporting Gap	(2) [-3, -1] Reporting Gap	(3) [-5, -1] Reporting Gap	(4) [-2, -1] Reporting Gap	(5) [-3, -1] Reporting Gap	(6) [-5, -1] Reporting Gap
LN(News)	-0.073***	-0.088***	-0.027***	-0.061***	-0.074***	-0.022**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
LN(Size)				0.015	0.017	0.012
				(0.02)	(0.02)	(0.02)
MTB				-0.012	-0.012	-0.012
				(0.01)	(0.01)	(0.01)
Return				-0.294	-0.313	-0.272
				(0.19)	(0.19)	(0.19)
Illiquidity				-0.013	-0.013	-0.014
				(0.02)	(0.02)	(0.02)
IVOL				0.009	0.010	0.008
				(0.02)	(0.02)	(0.02)
Earnings Month				0.041***	0.045***	0.041***
				(0.01)	(0.01)	(0.01)
Dividend Record				0.003	0.002	0.004
				(0.02)	(0.02)	(0.02)
Inst. Ownership				-0.197***	-0.199***	-0.194***
				(0.08)	(0.08)	(0.07)
Analyst Coverage				-0.002	-0.002	-0.002
				(0.02)	(0.02)	(0.02)
Constant	0.719***	0.718***	0.722***	0.692***	0.672**	0.737***
	(0.10)	(0.10)	(0.10)	(0.26)	(0.26)	(0.26)
Observations	14,847	14,847	14,847	7,905	7,905	7,905
Adjusted R-squared	0.235	0.240	0.230	0.244	0.248	0.240
Fixed Effects	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year

2.5 Conclusion

This paper examines how CEOs communicate with investors by trading their shares. I investigate whether news coverage and sentiment are associated with CEOs' trading patterns. I find that CEOs understand news about their firms better even after the private information is revealed to the market. They utilize information on the market's reaction to news dissemination to establish their share-trading strategies for the purpose of communicating with the investors.

Using insider trading data and media data for 2000 to 2016, I find that CEOs are more likely to purchase shares in the open market after positive and negative news releases. In addition, I find that these patterns vary conditional on firms' information environments. CEOs in firms with a transparent information environment (e.g., firms with either high analyst coverage or high search volume of the SEC EDGAR filings) are less likely to purchase shares after positive or negative news releases, suggesting that CEOs do not need to confirm firms' positive information and do need to mitigate the market overreaction to firms' negative news by performing open-market share purchases under the transparent information environment. Also, I find that CEOs have stronger incentives to correct the mispricing after negative news releases when firms have good governance, in terms of high institutional ownerships and high dedicated, transient, or quasi-indexer ownerships.

In addition, I find that CEOs selectively send signals to investors depending on the news categories. CEOs have stronger incentives to correct the mispricing in the cases of the market overreaction to negative hard news and market underreaction to positive soft news than in other scenarios. Moreover, I find that the CEOs' trading patterns have credibility and the market learns from their signals. Finally, and importantly, I find that CEOs intend to communicate with the market through their trading patterns, and pursuing profitability may not the only reason why CEOs trade shares in the open market. Overall, my results suggest that CEOs can make the news salient via their trading patterns.

2.6 Appendix

This internet appendix presents detailed summary statistics and additional analysis tables about the results of robustness tests using different sets of fixed effects to accompany the paper “Making News Salient.”

Table 2.1A Variable Definitions

News Variables	Definition	Source
LN(News)	Natural log of (1+News Coverage within [-5, -1], [-3, -1], or [-2, -1])	RavenPack News Analytics
LN(Pos_News)	Natural log of (1+ Number of cumulative positive news within [-5, -1], [-3, -1], or [-2, -1])	RavenPack News Analytics
LN(Neg_News)	Natural log of (1+ Number of cumulative negative news within [-5, -1], [-3, -1], or [-2, -1])	RavenPack News Analytics
LN(Neu_News)	Natural log of (1+ Number of cumulative neutral news within [-5, -1], [-3, -1], or [-2, -1])	RavenPack News Analytics
LN(Hard_Pos)	Natural log of (1+ Number of cumulative positive hard news within [-5, -1], [-3, -1], or [-2, -1])	RavenPack News Analytics
LN(Hard_Neg)	Natural log of (1+ Number of cumulative negative hard news within [-5, -1], [-3, -1], or [-2, -1])	RavenPack News Analytics
LN(Hard_Neu)	Natural log of (1+ Number of cumulative neutral hard news within [-5, -1], [-3, -1], or [-2, -1])	RavenPack News Analytics
LN(Soft_Pos)	Natural log of (1+ Number of cumulative positive soft news within [-5, -1], [-3, -1], or [-2, -1])	RavenPack News Analytics
LN(Soft_Neg)	Natural log of (1+ Number of cumulative negative soft news within [-5, -1], [-3, -1], or [-2, -1])	RavenPack News Analytics
LN(Soft_Neu)	Natural log of (1+ Number of cumulative neutral soft news within [-5, -1], [-3, -1], or [-2, -1])	RavenPack News Analytics
Ratio_Pos_News	Number of cumulative positive news/News Coverage	RavenPack News Analytics
Ratio_Neg_News	Number of cumulative negative news/News Coverage	RavenPack News Analytics
LN(News)	Natural log of (1+News Coverage within [-5, -1], [-3, -1], or [-2, -1])	RavenPack News Analytics
CEO Trading Variables		
Buy	An indicator of open market stock purchase	Thomson Insider Filing
Sell	An indicator of open market stock sales	Thomson Insider Filing

(Continued from the previous page)

Firm-Characteristics

LN(Size)	Natural log of (1+The firm's market capitalization at the prior year-end)	Compustat
MTB	Market-to-book ratio at the prior year-end	Compustat, CRSP
Return	Stock returns over the prior 12 months calculated using a monthly rolling window	CRSP
Illiquidity	The Amihud (2002) illiquidity measure, or the yearly average of the daily square root of (Price × Volume)/|Return|	CRSP
IVOL	The stock's annualized residual return from a regression of daily stock returns on the Fama-French three factors during the past year	CRSP
Earnings Month	A dummy variable equal to one if the firm announces quarterly earnings during the month	Compustat
Dividend Month	A dummy variable equal to one if there was a dividend record date during the month	CRSP
Institutional Ownership	The percentage of outstanding shares held by institutional investors	Thomson Reuters Institutional (13f) Holdings
Analyst Coverage	Natural log of (1+the number of analysts covering the firm over the one-year period ending on the most recent month-end before the transaction)	I/B/E/S
LN(Search Volume)	Natural log of (1+The firm's search volume via SEC Edgar system)	SEC Edgar
Cumulative Search (12 months)	Cumulative number of search volume in the previous 12 months	SEC Edgar
Transparent	An indication variable that is equal to one if the analyst coverage of the firm falls into the top quintile of the sample distribution, and zero otherwise	I/B/E/S
Active Information Acquisition	An indication variable that is equal to one if the cumulative search volume of the firm falls into the top quintile of the sample distribution, and zero otherwise	SEC Edgar
High Ownership	An indication variable that is equal to one if institutional ownership of the firm falls into the top quintile of the sample distribution, and zero otherwise	Thomson Reuters Institutional (13f) Holdings

Table 2.2A Trend in News Coverage and CEO Trading Pattern

Panel A. Trend in News Coverage

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
News Coverage	82086	132992	117963	120069	213981	217230	177339	308361	323058	300571	288181	355701	484174	544709	535396	541820	630069
Positive (ESS)	46916	58174	61449	62534	79555	82757	81220	130814	139808	124478	125538	164623	218845	241749	237180	248402	292205
	57.15%	43.74%	52.09%	52.08%	37.18%	38.10%	45.80%	42.42%	43.28%	41.41%	43.56%	46.28%	45.20%	44.38%	44.30%	45.85%	46.38%
Negative (ESS)	21566	34061	33864	30142	70550	76006	52154	101203	104506	101005	94040	113764	160229	191541	190247	190954	217234
	26.27%	25.61%	28.71%	25.10%	32.97%	34.99%	29.41%	32.82%	32.35%	33.60%	32.63%	31.98%	33.09%	35.16%	35.53%	35.24%	34.48%
Neutral (ESS)	13604	40757	22650	27393	63876	58467	43965	76344	78744	75088	68603	77314	105100	111419	107969	102464	120630
	16.57%	30.65%	19.20%	22.81%	29.85%	26.91%	24.79%	24.76%	24.37%	24.98%	23.81%	21.74%	21.71%	20.45%	20.17%	18.91%	19.15%
Positive (CSS)	29094	34340	35630	39404	54314	53297	50300	78905	86990	77172	82837	114381	159170	186342	199839	209051	220011
	35.44%	25.82%	30.20%	32.82%	25.38%	24.53%	28.36%	25.59%	26.93%	25.68%	28.74%	32.16%	32.87%	34.21%	37.33%	38.58%	34.92%
Negative (CSS)	19488	30450	29538	25784	73876	69563	49669	77081	77945	73667	65782	76100	102937	114948	110665	114312	114677
	23.74%	22.90%	25.04%	21.47%	34.52%	32.02%	28.01%	25.00%	24.13%	24.51%	22.83%	21.39%	21.26%	21.10%	20.67%	21.10%	18.20%
Neutral (CSS)	33504	68202	52795	54881	85791	94370	77370	152375	158123	149732	139562	165220	222067	243419	224892	218457	295381
	40.82%	51.28%	44.76%	45.71%	40.09%	43.44%	43.63%	49.41%	48.95%	49.82%	48.43%	46.45%	45.87%	44.69%	42.00%	40.32%	46.88%

Panel B. Trend in News Coverage by News Category

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Hard News Coverage	33885	60597	63799	60587	67309	69785	72732	91774	97769	92264	87057	95793	10968	10334	99982	11118	18904
	41.28	45.56	54.08	50.46	31.46	32.12	41.01	29.76	30.26	30.70	30.21	26.93	22.65	18.97	18.67	20.52	30.00
Positive News	20922	29954	31389	31592	37882	38174	40026	47837	46612	38081	44347	48729	54548	50160	47338	54408	96946
	61.74	49.43	49.20	52.14	56.28	54.70	55.03	52.12	47.68	41.27	50.94	50.87	49.73	48.54	47.35	48.93	51.28
Negative News	7904	17480	17624	15288	15860	16869	18822	26685	30918	32001	18231	21018	26469	26284	23405	28868	54522
	23.33	28.85	27.62	25.23	23.56	24.17	25.88	29.08	31.62	34.68	20.94	21.94	24.13	25.43	23.41	25.96	28.84
Neutral News	5059	13163	14786	13707	13567	14742	13884	17252	20239	22182	24479	26046	28672	26902	29239	27910	37579
	14.93	21.72	23.18	22.62	20.16	21.12	19.09	18.80	20.70	24.04	28.12	27.19	26.14	26.03	29.24	25.10	19.88
Positive News	10221	16470	17773	17945	24562	27790	28428	32075	31975	27579	34419	37897	39612	37222	38374	41631	76708
	30.16	27.18	27.86	29.62	36.49	39.82	39.09	34.95	32.70	29.89	39.54	39.56	36.11	36.02	38.38	37.44	40.58
Negative News	11133	21431	21407	17181	17669	17244	18439	26103	29971	29663	18352	20124	25886	24871	21426	26203	41113
	32.86	35.37	33.55	28.36	26.25	24.71	25.35	28.44	30.65	32.15	21.08	21.01	23.60	24.07	21.43	23.57	21.75
Neutral News	12531	22696	24619	25461	25078	24751	25865	33596	35823	35022	34286	37772	44191	41253	40182	43352	71226
	36.98	37.45	38.59	42.02	37.26	35.47	35.56	36.61	36.64	37.96	39.38	39.43	40.29	39.92	40.19	38.99	37.68
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Soft News Coverage	48201	72395	54164	59482	14667	14744	10460	21658	22528	20830	20112	25990	37448	44136	43541	43063	44102
	58.72	54.44	45.92	49.54	68.54	67.88	58.99	70.24	69.74	69.30	69.79	73.07	77.35	81.03	81.33	79.48	70.00
Positive News	25994	28220	30060	30942	41673	44583	41194	82977	93196	86397	81191	11589	16429	19158	18984	19399	19525
	53.93	38.98	55.50	52.02	28.41	30.24	39.38	38.31	41.37	41.48	40.37	44.59	43.87	43.41	43.60	45.05	44.27
Negative News	13662	16581	16240	14854	54690	59137	33332	74518	73588	69004	75809	92746	13376	16525	16684	16208	16271
	28.34	22.90	29.98	24.97	37.29	40.11	31.86	34.41	32.66	33.13	37.69	35.68	35.72	37.44	38.32	37.64	36.89
Neutral News	8545	27594	7864	13686	50309	43725	30081	59092	58505	52906	44124	51268	76428	84517	78730	74554	83051
	17.73	38.12	14.52	23.01	34.30	29.66	28.76	27.28	25.97	25.40	21.94	19.73	20.41	19.15	18.08	17.31	18.83
Positive News	18873	17870	17857	21459	29752	25507	21872	46830	55015	49593	48418	76484	11955	14912	16146	16742	14330
	39.15	24.68	32.97	36.08	20.28	17.30	20.91	21.62	24.42	23.81	24.07	29.43	31.93	33.79	37.08	38.88	32.49
Negative News	8355	9019	8131	8603	56207	52319	31230	50978	47974	44004	47430	55976	77051	90077	89239	88109	73564
	17.33	12.46	15.01	14.46	38.32	35.48	29.85	23.54	21.29	21.12	23.58	21.54	20.58	20.41	20.50	20.46	16.68
Neutral News	20973	45506	28176	29420	60713	69619	51505	11877	12230	11471	10527	12744	17787	20216	18471	17510	22415
	43.51	62.86	52.02	49.46	41.39	47.22	49.24	54.84	54.29	55.07	52.34	49.04	47.50	45.80	42.42	40.66	50.83

Panel C. Summary Statistics (Daily-level)

News Variables	N	Mean	SD	P25	P50	P75	Source
LN(News) [-2, -1]	13,873,842	0.2300	0.4870	0	0	0	RavenPack News Analytics
LN(Pos_News) [-2, -1]	13,873,842	0.0892	0.2860	0	0	0	RavenPack News Analytics
LN(Neg_News) [-2, -1]	13,873,842	0.0668	0.2400	0	0	0	RavenPack News Analytics
LN(Neu_News) [-2, -1]	13,873,842	0.1230	0.3380	0	0	0	RavenPack News Analytics
LN(Hard_Pos) [-2, -1]	13,873,842	0.0289	0.1720	0	0	0	RavenPack News Analytics
LN(Hard_Neg) [-2, -1]	13,873,842	0.0205	0.1420	0	0	0	RavenPack News Analytics
LN(Hard_Neu) [-2, -1]	13,873,842	0.0297	0.1810	0	0	0	RavenPack News Analytics
LN(Soft_Pos) [-2, -1]	13,873,842	0.0651	0.2310	0	0	0	RavenPack News Analytics
LN(Soft_Neg) [-2, -1]	13,873,842	0.0485	0.1950	0	0	0	RavenPack News Analytics
LN(Soft_Neu) [-2, -1]	13,873,842	0.0973	0.2910	0	0	0	RavenPack News Analytics
LN(News) [-3, -1]	13,873,842	0.3070	0.5540	0	0	0.693	RavenPack News Analytics
LN(Pos_News) [-3, -1]	13,873,842	0.1200	0.3320	0	0	0	RavenPack News Analytics
LN(Neg_News) [-3, -1]	13,873,842	0.0912	0.2800	0	0	0	RavenPack News Analytics
LN(Neu_News) [-3, -1]	13,873,842	0.1650	0.3900	0	0	0	RavenPack News Analytics
LN(Hard_Pos) [-3, -1]	13,873,842	0.0380	0.1970	0	0	0	RavenPack News Analytics
LN(Hard_Neg) [-3, -1]	13,873,842	0.0272	0.1640	0	0	0	RavenPack News Analytics
LN(Hard_Neu) [-3, -1]	13,873,842	0.0385	0.2060	0	0	0	RavenPack News Analytics
LN(Soft_Pos) [-3, -1]	13,873,842	0.0895	0.2730	0	0	0	RavenPack News Analytics
LN(Soft_Neg) [-3, -1]	13,873,842	0.0673	0.2310	0	0	0	RavenPack News Analytics
LN(Soft_Neu) [-3, -1]	13,873,842	0.1330	0.3400	0	0	0	RavenPack News Analytics
LN(News) [-5, -1]	13,873,842	0.4500	0.6570	0	0	0.6930	RavenPack News Analytics
LN(Pos_News) [-5, -1]	13,873,842	0.1810	0.4060	0	0	0	RavenPack News Analytics
LN(Neg_News) [-5, -1]	13,873,842	0.1400	0.3470	0	0	0	RavenPack News Analytics
LN(Neu_News) [-5, -1]	13,873,842	0.2480	0.4720	0	0	0.6930	RavenPack News Analytics
LN(Hard_Pos) [-5, -1]	13,873,842	0.0591	0.2450	0	0	0	RavenPack News Analytics
LN(Hard_Neg) [-5, -1]	13,873,842	0.0427	0.2050	0	0	0	RavenPack News Analytics
LN(Hard_Neu) [-5, -1]	13,873,842	0.0602	0.2560	0	0	0	RavenPack News Analytics
LN(Soft_Pos) [-5, -1]	13,873,842	0.1350	0.3360	0	0	0	RavenPack News Analytics
LN(Soft_Neg) [-5, -1]	13,873,842	0.1030	0.2890	0	0	0	RavenPack News Analytics
LN(Soft_Neu) [-5, -1]	13,873,842	0.2000	0.4160	0	0	0	RavenPack News Analytics

Panel D. Summary Statistics (Transaction-level)

	N	Mean	SD
Exercise	142,487	0.396	0.489
Sell	142,487	0.681	0.466
Buy	142,487	0.194	0.396
Exercise-and-Sell	142,487	0.267	0.442
Company Disposition	142,487	0.035	0.182
Exercise-and-Hold	142,487	0.095	0.293
MTB	140,358	2.78	3.570
LN(Size)	141,496	13.48	1.911
Return	141,496	0.023	0.067
Analyst Coverage	128,582	3.132	1.131
Institutional Ownership	81,841	0.620	0.300
Earnings Announcement Month	142,487	0.331	0.471
Dividend Record Month	142,487	0.114	0.318
IVOL	140,081	0.440	0.352
Illiquidity	142,096	0.164	0.560
CAR[0, 2]	140,765	0.006	0.066
CAR[0, 3]	140,765	0.007	0.075
CAR[0, 5]	140,765	0.008	0.087

Table 2.3A News Coverage and CEO Trading Patterns

$$\text{OLS: } \mathrm{Y_{it}} = \beta_0 + \beta_1 \mathrm{X_1} + \beta_2 \mathrm{X_2} + \cdots + \beta_k \mathrm{X_k} + \mu_i + \upsilon_t + \varepsilon_{it}$$

This table contains OLS regressions that examine the relation between news coverage and CEO trading pattern. Dependent variables are CEO share purchase (sale) indicator variables, which are equal to 1 if CEO performs open market share purchase (sales). Key independent variable is news coverage variable. LN(Coverage) is natural logarithm of 1 + number of news coverage within a window, which specifies on the top of the table. Control variables include annualized stock returns, natural logarithm of firm size, idiosyncratic volatility, Market-to-Book ratio, The Amihud illiquidity measure, earnings announcement month indicator, dividend record month indicator, institutional ownership, and analyst coverage. In the model, μ_i means each firm's time-invariant specific effect, and ν_t means that year specific effect. X_{it} is a set of explanatory variables, and ε_{it} is an error term, which assumes that $E(\varepsilon_{it})=0$ and $Var(\varepsilon_{it})=\sigma^2$. All models include time and firm fixed effects and cluster standard errors by both firm and year. Brackets contain robust t-statistics and superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

(Continued from the previous page)

Panel A: News Coverage and CEO Trading Patterns (Transaction-level)

	(1) [-2, -1] Buy	(2) [-2, -1] Buy	(3) [-3, -1] Buy	(4) [-3, -1] Buy	(5) [-5, -1] Buy	(6) [-5, -1] Buy
LN(Coverage)	-0.003**	0.004**	0.001	0.007***	0.003	0.011***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LN(Size)		-0.107***		-0.107***		-0.108***
		(0.01)		(0.01)		(0.01)
MTB		-0.003		-0.003		-0.002
		(0.00)		(0.00)		(0.00)
Return		-0.863***		-0.861***		-0.860***
		(0.08)		(0.08)		(0.08)
Illiquidity		0.036**		0.036**		0.036**
		(0.02)		(0.02)		(0.02)
IVOL		0.067***		0.066***		0.066***
		(0.01)		(0.01)		(0.01)
Earnings Month		0.017***		0.017***		0.015***
		(0.00)		(0.00)		(0.00)
Dividend Record Month		0.009		0.009		0.009
		(0.01)		(0.01)		(0.01)
Institutional Ownership		-0.002		-0.001		-0.000
		(0.02)		(0.02)		(0.02)
Analyst Coverage		0.014*		0.014*		0.014*
		(0.01)		(0.01)		(0.01)
Constant	0.272***	1.629***	0.272***	1.635***	0.271***	1.643***
	(0.02)	(0.14)	(0.02)	(0.14)	(0.02)	(0.14)
Observations	124,639	65,396	124,639	65,396	124,639	65,396
Adjusted R-squared	0.673	0.749	0.673	0.749	0.673	0.749
Control Variables	No	Yes	No	Yes	No	Yes
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year

(Continued from the previous page)

Panel B: News Coverage and CEO Share Sales (Daily-level)

	(1) [-2, -1] Sell	(2) [-2, -1] Sell	(3) [-3, -1] Sell	(4) [-3, -1] Sell	(5) [-5, -1] Sell	(6) [-5, -1] Sell
LN(News)	0.004***	0.004***	0.005***	0.004***	0.006***	0.006***
	(7.60)	(5.57)	(8.26)	(6.36)	(9.40)	(7.65)
LN(Size)		0.004***		0.003***		0.003***
		(10.56)		(10.25)		(9.42)
MTB		0.000		0.000		0.000
		(1.08)		(1.09)		(1.14)
Return		0.033***		0.033***		0.033***
		(4.64)		(4.65)		(4.64)
Illiquidity		0.001***		0.001***		0.001***
		(5.85)		(5.50)		(4.52)
IVOL		0.001**		0.001**		0.001*
		(3.00)		(2.79)		(2.05)
Earnings Month		-0.000		-0.001**		-0.001***
		(-1.66)		(-2.21)		(-3.75)
Dividend Record Month		0.001**		0.001**		0.000
		(2.50)		(2.32)		(1.72)
Institutional Ownership		0.000		0.000		0.001
		(0.04)		(0.16)		(0.39)
Analyst Coverage		0.001*		0.001*		0.001*
		(2.06)		(1.99)		(1.79)
Constant	0.006***	-0.044***	0.006***	-0.043***	0.004***	-0.041***
	(48.37)	(-10.10)	(31.40)	(-9.87)	(13.85)	(-9.28)
Observations	13,824,801	6,955,190	13,824,801	6,955,190	13,824,801	6,955,190
Adjusted R-squared	0.033	0.044	0.033	0.045	0.034	0.046
Fixed Effect	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year

Table 2.4A: News Tone and CEO Trading Patterns

$$\text{LPM: } \Pr(Y = 1 | X_1, X_2, \dots, X_k) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k$$

This table contains OLS regressions that examine the relation between new tone and CEO trading pattern. Dependent variable for columns (1), (3), and (5) is CEO share purchase indicator variable, which is equal to 1 if CEO performs open market share purchase. Dependent variable for the other columns is CEO share sales indicator variable, which is equal to 1 if CEO performs open market share sales. Key independent variables are news coverage variables by news tone. LN(Pos_News) is natural logarithm of 1 + number of positive news coverage, based on event sentiment score (ESS), within a window, which specifies on the top of the table. LN(Neg_News) is natural logarithm of 1 + number of negative news coverage, based on event sentiment score (ESS), within a window, which specifies on the top of the table. LN(Coverage) is natural logarithm of 1 + number of news coverage within a window, which specifies on the top of the table. Control variables include annualized stock returns, natural logarithm of firm size, idiosyncratic volatility, Market-to-Book ratio, The Amihud illiquidity measure, earnings announcement month indicator, dividend record month indicator, institutional ownership, and analyst coverage. In the model, μ_i means each firm's time-invariant specific effect, and v_t means that year specific effect. X_{it} is a set of explanatory variables, and ε_{it} is an error term, which assumes that $E(\varepsilon_{it})=0$ and $Var(\varepsilon_{it})=\sigma^2$. All models include time and firm fixed effects and cluster standard errors by both firm and year. Brackets contain robust t-statistics and superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Panel A: News Tone and CEO Trading Patterns (Transaction-level)

	(1)	(2)	(3)	(4)	(5)	(6)
	[-2, -1]	[-2, -1]	[-3, -1]	[-3, -1]	[-5, -1]	[-5, -1]
	Buy	Buy	Buy	Buy	Buy	Buy
LN(Pos_News)	0.073***	0.045***	0.074***	0.047***	0.070***	0.047***
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
LN(Neg_News)	0.022***	0.018***	0.024***	0.020***	0.028***	0.021***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LN(Coverage)	-0.041***	-0.022***	-0.040***	-0.021***	-0.041***	-0.020***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LN(Size)		-0.107***		-0.108***		-0.109***
		(0.01)		(0.01)		(0.01)
MTB		-0.002		-0.002		-0.002
		(0.00)		(0.00)		(0.00)
Return		-0.855***		-0.851***		-0.845***
		(0.08)		(0.08)		(0.08)
Illiquidity		0.035**		0.034**		0.033**
		(0.02)		(0.02)		(0.02)
IVOL		0.067***		0.066***		0.065***
		(0.01)		(0.01)		(0.01)
Earnings Month		0.015***		0.014***		0.012***
		(0.00)		(0.00)		(0.00)
Dividend Record Month		0.009		0.010		0.009
		(0.01)		(0.01)		(0.01)
Institutional Ownership		-0.000		0.001		0.001
		(0.02)		(0.02)		(0.02)
Analyst Coverage		0.014*		0.014*		0.014*
		(0.01)		(0.01)		(0.01)
Constant	0.273***	1.635***	0.274***	1.642***	0.275***	1.655***
	(0.02)	(0.14)	(0.02)	(0.14)	(0.02)	(0.14)
Observations	124,639	65,396	124,639	65,396	124,639	65,396
Adjusted R-squared	0.675	0.749	0.675	0.750	0.676	0.750
Control Variables	No	Yes	No	Yes	No	Yes
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year

Panel B: News Tone and CEO Share Sales (Daily-level)

	(1)	(2)	(3)	(4)	(5)	(6)
	[-2, -1]	[-2, -1]	[-3, -1]	[-3, -1]	[-5, -1]	[-5, -1]
	Sell	Sell	Sell	Sell	Sell	Sell
LN(Pos_News)	-0.002***	-0.002**	-0.001***	-0.001**	-0.000	-0.000
	(-3.64)	(-2.84)	(-3.17)	(-2.48)	(-1.07)	(-0.38)
LN(Neg_News)	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	(4.82)	(4.01)	(4.92)	(4.04)	(5.07)	(4.04)
LN(Neu_News)	0.004***	0.004***	0.005***	0.004***	0.006***	0.006***
	(8.61)	(6.61)	(9.26)	(7.44)	(10.39)	(9.24)
LN(Size)		0.004***		0.003***		0.003***
		(10.56)		(10.25)		(9.39)
MTB		0.000		0.000		0.000
		(1.07)		(1.09)		(1.14)
Return		0.033***		0.033***		0.033***
		(4.63)		(4.64)		(4.63)
Illiquidity		0.001***		0.001***		0.001***
		(6.05)		(5.79)		(4.85)
IVOL		0.001**		0.001**		0.001**
		(3.01)		(2.83)		(2.16)
Earnings Month		-0.000		-0.001**		-0.001***
		(-1.69)		(-2.24)		(-4.05)
Dividend Record Month		0.001**		0.000**		0.000
		(2.47)		(2.30)		(1.73)
Institutional Ownership		-0.000		0.000		0.001
		(-0.01)		(0.09)		(0.36)
Analyst Coverage		0.001*		0.001*		0.001*
		(2.02)		(1.96)		(1.79)
Constant	0.006***	-0.044***	0.006***	-0.043***	0.005***	-0.041***
	(67.47)	(-10.03)	(44.89)	(-9.77)	(20.39)	(-9.05)
Observations	13,824,801	6,955,190	13,824,801	6,955,190	13,824,801	6,955,190
Adjusted R-squared	0.033	0.045	0.033	0.045	0.034	0.046
Fixed Effect	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year

Chapter 3:

Does Bank Competition Increase Bank Liquidity Creation?

A State-Level Perspective

3.1 Introduction

This paper examines whether enhanced bank competition, following staggered bank deregulation events in the United States, is associated with bank liquidity creation at the macro-level. How do banks react to these state-level staggered shocks? Surprisingly, I find that bank competition does not, on average, significantly affect state-level bank liquidity creation, while bank-level analysis shows that bank competition decreases bank liquidity creation. I also find that heterogenous banks and markets respond to the bank deregulation differently.

Past literature on bank deregulation demonstrates that bank competition positively affects local economies in various ways. Previous studies find that enhanced bank competition following bank deregulation increases local economic growth, new incorporation in the deregulated states, small firm finance, and firm total factor productivity (TFP) (e.g., Jayaratne and Strahan 1996; Black and Strahan 2002; Cetorelli and Strahan 2006; Rice and Strahan 2010; Krishnan, Nandy, and Puri 2014).

However, the empirical results do not show whether the effects of bank competition on local economies are driven by bank-side channels, including bank liquidity creation. Bank liquidity creation is a crucial activity of banks and has significant implications for local economies in terms of the ease, cost, and time for local market participants to raise funds from banks in the market. In addition, bank liquidity creation is a better indicator to predict state-level real economic output than bank asset measures (e.g., Berger and Sedunov 2017), so it is important to investigate the relation between bank competition and bank liquidity creation.

Jiang, Levine, and Lin (2019) find that bank competition reduces bank liquidity creation at the bank level. However, from a social welfare perspective, it is extremely important to investigate the effects of bank competition on bank liquidity creation at the macro level. Because regulators institute bank deregulation to encourage depressed local capital markets and local economies, the state-level perspective could prove valuable in evaluating the policy implications of deregulation. Thus, in this paper, I provide aggregated state-level evidence to address whether the positive effects of bank competition on local economies is driven by the crucial bank activity of bank liquidity creation. In particular, I examine whether enhanced bank competition following bank deregulation events in the United States increases bank liquidity creation at the state level. In addition, I investigate whether there are heterogeneous effects of bank competition on bank liquidity creation depending on bank characteristics and market characteristics.

Following previous studies assessing the U.S. interstate banking deregulation and interstate bank branching deregulation as exogenous shocks on bank competition (e.g., Johnson and Rice 2008; Rice and Strahan 2010; Koetter, Kolari, and Spierdijk 2012; Chava, Oettl, Subramanian, and Subramanian 2013; Krishnan, Nandy, and Puri 2014; Cornaggia, Mao, Tian, and Wolfe 2015), I exploit the exogenous variation in state-level bank competition following staggered interstate bank deregulation and interstate bank branching deregulation events in the United States.

I exclude intrastate bank deregulation events from analysis because these events occurred primarily before 1984, which is the starting date of my sample period. Interstate bank deregulation, which chiefly occurred in the 1980s and 1990s, allows banks to acquire or establish a charter in deregulated states. It does not allow banks to expand their branches across states. More important, the Riegle-Neale Interstate Banking and Branching Efficiency Act (IBBEA) of 1994 allows banks to acquire or establish a branch as well as a charter in deregulated states. However, the U.S. government gives each state the authority to erect its own barriers, such as statewide resulted deposit caps after the acquisition or establishment, minimum age of targets, de novo interstate branching, the acquisition of individual branches, and reciprocity. These deregulation events allow me to investigate different perspectives of the government policies.

The important advantage of a difference-in-differences approach, exploiting bank deregulation events, is that I can mitigate endogeneity concerns such as reverse causality and omitted variables. It is possible that states that create more liquidity may have less competition. Moreover, aggregate state-level bank liquidity creation could affect bank competition within a state because regulators may implement the policy based on poor liquidity creation within a state. Exploiting state-level regulatory changes could mitigate this issue because staggered bank deregulation events exogenously increase bank competition. This allows me to disentangle the effect of bank competition on bank liquidity creation from other factors that are correlated with liquidity creation strategies. I estimate the effect of bank deregulation in deregulated states, which are treated states, on bank liquidity creation by comparing the difference in bank liquidity creation in treated states before and after the deregulation with the difference in bank liquidity creation in control states before and after the deregulation. Especially, the staggered nature of bank deregulation events means that control states are not limited to states that are never deregulated.

However, as the literature on bank deregulation and political connection shows, external pressures may drive the implementation of government policies, such as bank deregulation and the Troubled Asset Relief Program (TARP) (e.g., Kroszner and Strahan 1999; Mian, Sufi, and Trebbi 2010; Duchin and Sosyura 2012). This suggests that my results may be driven by reverse causality even though I identify change in bank competition through staggered bank deregulation events. To mitigate this issue, following Bertrand and Mullainathan (2003), I examine the dynamic effects of interstate bank deregulation and interstate bank branching deregulation on state-level bank liquidity creation.

A challenge also exists regarding omitted variables, as unobservable variables that coincide with the bank deregulation events may result in changes in bank liquidity creation. However, a staggered characteristic of bank deregulation events across states can mitigate the omitted variable bias because omitted variables that are not related to deregulation events would not demonstrate the same patterns, with multiple shocks occurring in different states at different times.

I study state-level bank liquidity, created by almost all commercial banks in the United States from 1984 to 2006. Surprisingly, I find that bank competition does not, on average, significantly affect state-level bank liquidity creation, while the effects of bank competition on state-level bank liquidity creation vary depending on liquidity components, bank size, geographic area, and banks' home state status. In addition, I find different effects of two different regulatory changes on bank liquidity creation in a sub-sample analysis.

To be specific, I examine whether relationships between bank competition and bank liquidity creation vary depending on bank liquidity components, such as asset-side liquidity creation, liability-side liquidity creation, and off-balance sheet liquidity creation. I find that interstate bank deregulation increases only asset-side bank liquidity creation and that interstate bank branching deregulation does not significantly affect components of liquidity creation after controlling for state-level macroeconomic variables and state characteristics. The results suggest that the relationship between bank competition and bank liquidity creation vary in different liquidity creation components.

I then investigate whether bank size is associated with the relationship. I find that interstate banking deregulation increases only state-level bank liquidity created by medium-sized banks and that interstate bank branching deregulation decreases state-level bank liquidity created by small and medium-sized banks. The results suggest that enhanced bank competition through two regulatory events affects state-level bank liquidity creation differently according to the size of banks that create liquidity in the market.

Next, I analyze whether a bank's geographic location plays a role in the relationship between bank competition and state-level bank liquidity creation. I find that enhanced bank competition following interstate banking deregulation increases state-level bank liquidity created by bank branches that locate in non-Metropolitan Statistical Areas (MSAs), and also that enhanced bank competition following the enactment of IBBEA decreases state-level liquidity created by bank branches located in non-MSAs. I find no significant results for state-level liquidity created by MSA branches. These results suggest that there are heterogeneous effects of bank competition on state-level liquidity creation depending on a bank's location.

Finally, I examine whether bank's headquarter location is associated with the relationship between bank competition and liquidity creation at the state level. I find that only interstate bank deregulation increases state bank liquidity created by banks whose headquarters are located in the deregulated states. Jiang, Levine, and Lin (2019) explore how banks that are headquartered in the deregulated states respond to the exogenous shocks and find that interstate bank deregulation decreases bank liquidity creation at the bank level. Together with their result, my result suggests that banks reallocate resources when home market competition increases. They create more liquidity in the deregulated market, while they create less liquidity in other markets. I find no significant evidence that interstate bank deregulation affects state-level liquidity created by banks headquartered outside the deregulated states and that interstate bank branching deregulation affects state-level bank liquidity creation regardless of bank headquarter location.

In addition, throughout the analysis, I find that signs of coefficients in two bank deregulation variables indicate quite the opposite, suggesting that interstate banking deregulation and interstate bank branching deregulation have different effects and implications on state-level bank liquidity creation.

My findings suggest that one government policy applied to all heterogeneous banks and states in the same way does not suit all circumstances. Thus, the results imply that regulators should consider designing new policies regarding bank competition depending on banks' and markets' heterogeneity to encourage local capital markets and economic growth.

My paper contributes to the literature that investigates the effects of banking deregulation. Although the previous literature shows that bank deregulation events affect local economic growth and corporate policies, the results of my paper suggest that the effects might not be driven by banking activities because bank liquidity creation would be crucial bank-side activity to encourage local market growth.

Second, my paper contributes to the literature on bank liquidity creation. Because of a lack of comprehensive bank liquidity creation measures, there are few empirical studies examining the determinants of bank liquidity creation and/or the effects of bank liquidity creation before the comprehensive measure provided by Berger and Bouwman (2009). The literature studies relationships between liquidity creation and equity ratio (e.g., Berger and Bouwman 2009), bank regulatory capital (e.g., Distinguin, Roulet, and Tarazi 2013), regulatory interventions and capital support (e.g., Berger, Bouwman, Kick, and Schaeck 2016), monetary policy and financial crises (e.g., Berger and Bouwman 2017), corporate governance (e.g., Díaz and Huang 2017), and real economic output (e.g., Berger and Sedunov 2017). Also, Berger, Guedhami, Kim, and Li (2018) is a closely related study that investigate the relation between bank liquidity hoarding and economic policy uncertainty.

I am aware of a contemporaneous study by Jiang, Levine, and Lin (2019), which also examines the relationship between bank competition and bank liquidity creation. Based on interstate bank deregulation, they construct distance-weighted bank competition measures, which are continuous bank-level measures. Their measure considers the distance between each bank in the deregulated state and capital cities of the other states as factors of bank competition. Using the bank-level distance-weighted interstate deregulation measures, they find that regulatory-induced competition has a negative effect on bank liquidity creation.

In contrast to this study, I focus on state-level analysis. State-level analysis allows me to generate policy implications on bank competition. In addition, I exploit interstate bank branching deregulation, which would be more important for bank liquidity creation because decisions about loan and deposit contracts are made by branch managers. Although a commercial bank may be located in close proximity to the capital city of a deregulated state, small banks may not be affected by interstate bank deregulation because they lack sufficient resources to acquire/establish a charter in the deregulated state, so it will be important to explore whether both interstate bank deregulation and interstate bank branching deregulation affect bank liquidity creation in the same way. Thus, same as Chava, Oettl, Subramanian, and Subramanian (2013) and Cornaggia, Mao, Tian, and Wolfe (2015), my paper and Jiang, Levine, and Lin (2019) suggest two different perspectives on bank deregulation.

3.2 Literature Review

3.2.1 Bank Competition

The deregulation of banking activities has attracted much attention from researchers and regulators on the role of competition in the banking industry. Previous literature about bank competition mostly focused on the impact of bank competition on financial stability, risk-taking, access to credit, and bank failure. However, insufficient discussion has taken place regarding the effect of bank competition on bank liquidity creation.

Two strands of research exist on bank competition, "competition-fragility" and "competition-stability." The "competition-fragility" view suggests that enhanced bank competition results in reduced profit margins and franchise value, and that this induces banks to take excessive risks. According to past literature on this view, profit margins act as safeguards in the event of financial distress, so banks try to recover their profit margins by taking excessive risks (e.g., Repullo 2004). Moreover, banks tend to protect their franchise value when the market is more concentrated by taking fewer risks because high franchise value implies high opportunity costs of bank failure (e.g., Keeley 1990; Hellmann, Murdock, and Stiglitz 2000). Thus, the "competition-fragility" view supports the argument that higher levels of bank competition would result in more fragility.

Conversely, the "competition-stability" view argues that bank competition makes financial systems more stable. That is, more concentrated market power may lead to higher levels of bank risk and/or higher probabilities of bank failure. Past literature supporting the "competition-stability" view argues that the greater a bank's market power, the greater its risk exposure. This is because the dominant banks enjoy monopolistic rents, such as higher interest rates and lower deposit rates, through their market power, which could lead to adverse selection and risk shifting (e.g., Stiglitz and Weiss 1981). Boyd and

De Nicoló (2005) and Schaeck, Cihak, and Wolfe (2009) also support the "competition-stability" view. These studies suggest that the more market power exists, the less stable a financial system is. In contrast to previous studies, Boyd and De Nicoló (2005) construct models that allow bank competition for both deposit and loan markets, and they suggest the reverse relationship between bank competition and bank failure. Less bank competition means more concentrated market power and may lead to higher loan rates and lower deposit rates, because banks with higher levels of market power have incentives to pursue monopolistic rents. Reduced bank competition could lead to either a more stable credit market, which is an intended result of government policy, or a highly dominated and limited credit market, which is an unexpected incident. Using the international data of 45 countries, Schaeck, Cihak, and Wolfe (2009) also support this view. They find that enhanced bank competition tends to produce a more stable environment that tends not to suffer systemic crises.

However, Berger, Klapper, and Turk-Ariss (2009) take a moderate position, finding mixed empirical results concerning the relationship between bank competition and financial stability. Using a variety of risk and competition measures derived from a dataset of banks located in 23 countries, they find that market power increases credit risk, but that banks with more market power face less risk overall. Thus, the paper suggests limited support for both the competition-fragility and the competition-stability views. These mixed results suggest that the relationships between bank competition and bank activities could also be mixed under heterogeneous circumstances.

3.2.2 Bank Liquidity Creation

Many previous studies suggest that the reason banks exist is to create liquidity for borrowers and lenders (e.g., Bryant 1980; Diamond and Dybvig 1983; Gorton and

Pennacchi 1990; Holmström and Tirole 1998; Kashyap, Rajan, and Stein 2002; Gatev and Strahan 2006). Banks create liquidity because they grant long-term and illiquid loans to borrowers by using short-term and liquid deposits. Bryant (1980) and Diamond and Dybvig (1983) argue that banks create liquidity on the balance sheet by financing relatively illiquid assets with relatively liquid liabilities. Additionally, Holmström and Tirole (1998) and Kashyap, Rajan, and Stein (2002) document that banks also create liquidity in the form of loan commitments or credit lines, suggesting that banks create liquidity off the balance sheet as well. Loan commitments can give a borrower the option to draw down on loan funds on demand during the period of the contract. These withdrawals are uncertain for the bank. From the perspectives of customers, loan commitments provide liquidity whenever they require it unexpectedly. Furthermore, from the perspective of banks, Donaldson, Piacentino, and Thakor (2018) document how banks create funding liquidity. Their model implies that bank capital is positively related to bank liquidity creation.

Despite the importance of bank liquidity creation, the absence of a comprehensive measure for its creation prevents empirical studies examining theoretical views of bank liquidity creation. As a result, empirical studies regarding the role of banks as liquidity creators are relatively rare. Deep and Schaefer (2004) develop the liquidity transformation gap as a measure of liquidity creation, but it is not a comprehensive measure. Berger and Bouwman (2009) provide four measures of liquidity creation and argue that the "cat fat" measure is better than other measures, including the liquidity transformation gap, which is similar to Berger and Bouwman's "mat nonfat" measure. In contrast to the liquidity transformation gap, the "cat fat" liquidity creation measure classifies loans by category rather than by maturity. This measure treats business loans as illiquid regardless of their maturity because banks generally cannot easily dispose of them to meet liquidity needs, while it treats residential mortgages and consumer loans as semi-liquid because they can often be securitized and sold to meet demands for liquid funds. Moreover, “cat fat” includes off-balance sheet activities as well as on-balance sheet activities. Thus, the “cat fat” measure is a more comprehensive and advanced measure of liquidity creation.

Berger and Bouwman (2009) construct a comprehensive measure of bank liquidity creation by including off-balance sheet items and by considering categories rather than maturities. There is a three-step procedure for constructing liquidity creation measures. In Step 1, all on-balance sheet and off-balance sheets activities are classified as liquid, semi-liquid, or illiquid. The classification is based on the ease, cost, and time necessary for customers to obtain liquid funds from the bank, and the ease cost, and time necessary for banks to dispose of their obligations to meet these liquidity demands. The balance sheet items are classified by product category and maturity. In Step 2, weights are assigned to the items classified in Step 1. In Step 3, liquidity creation is measured by combining the items as classified in Step 1 and as weighted in Step 2.

By examining virtually all U.S. commercial banks from 1993 to 2003, Berger and Bouwman find that the U.S. banking industry created \$2.84 trillion in liquidity in 2003, which is equivalent to \$4.56 of liquidity creation per \$1 of bank equity capital, and liquidity creation has grown substantially over the sample period by using the “cat fat” measure. They also report that liquidity creation differs considerably among banks of different sizes. Banks categorized as large banks, approximately 2 percent of their sample, account for 81 percent of bank liquidity creation. In addition, off-balance sheet items play a significant role in generating liquidity for banks of all sizes.

Even though Berger and Bouwman (2009) provide the comprehensive liquidity creation measures, there are still not enough empirical studies exploring the role of banks as liquidity creators. The literature studies the relationship between liquidity creation and equity ratio (e.g., Berger and Bouwman 2009), bank regulatory capital (e.g., Distinguin, Roulet, and Tarazi 2013), regulatory interventions and capital support (e.g., Berger, Bouwman, Kick, and Schaeck 2016), monetary policy and financial crises (e.g., Berger and Bouwman 2017), corporate governance (Díaz and Huang 2017), and real economic output (Berger and Sedunov 2017).

There are also few studies examining the relationship between bank competition and bank liquidity creation, but these studies are different from my study. Joh and Kim (2008) and Horvath, Seidler, and Weill (2013) use non-U.S. data to investigate the relationship between bank competition and bank liquidity creation. Horvath, Seidler, and Weill (2013) investigate this research question using a dataset of Czech banks from 2002 to 2010. They find that enhanced competition reduces liquidity creation and suggest that pro-competitive policies in the banking industry can reduce liquidity provision by banks. However, they do not use the "cat fat" measure, which is the most comprehensive liquidity creation measure, because of a lack of data on components of this measure.

Joh and Kim (2008) use international data covering 25 Organisation for Economic Cooperation and Development (OECD) countries. They use the "cat fat" measure following Berger and Bouwman (2009) but they control for size and market shares even though the key explanatory variable is the Lerner Index, which is strongly related to those variables. This could lead to biased results.

Unlike these studies, my paper investigates whether bank competition is associated with bank liquidity creation, using the U.S. banking industry dataset. Additionally, to find causal relationships, I examine exogenous variations in bank competition through the U.S. banking deregulation events, including interstate bank deregulation and interstate branching deregulation, and use the "cat fat" measure with sufficient datasets.

Jiang, Levine, and Lin (2019) examine the effects of bank competition on bank liquidity creation. Based on interstate bank deregulation, they construct distance-weighted bank competition measures, which are continuous bank-level measures. Their measure considers the distance between each bank in the deregulated state and capital cities of the other states as factors of bank competition. Using the bank-level distance-weighted interstate deregulation measures, they find that regulatory-induced competition has a negative effect on bank liquidity creation.

In contrast to this study, I focus on both state-level and bank-level analyses that examine whether bank competition is related to bank liquidity creation. State-level analysis allows me to generate policy implications on bank competition. I also study interstate bank branching deregulation, which would be more important for bank liquidity creation because decisions about loan and deposit contracts are made by branch managers.

3.3 Data and Methodology

My sample consists of an unbalanced panel of bank-level datasets for almost all commercial banks in the United States during the sample period between 1984 and 2006.

Financial data from Call Reports covers the period between 1976 and 2016. However, my sample starts in 1984 because of missing observations before 1984 for items required to construct liquidity creation measures. In addition, following Berger and Bouwman (2009), I impose several restrictions to include only valid commercial banks in my sample. First, I exclude a bank with zero commercial real estate or commercial and industrial loans. Second, I exclude a bank with zero deposits. Third, I exclude zero or negative equity capital in the current or lagged year. Fourth, I exclude a bank whose average lagged gross total assets (GTA) are below $25 million. Fifth, I exclude a bank that has four times more unused commitments than GTA. Finally, I exclude a bank that resembles a thrift bank or a credit card bank.[6] Based on the restrictions above, Berger and Bouwman (2009) construct four different liquidity creation measures and the bank liquidity creation date is publicly available at Christa Bouwman's personal website.[7]

To obtain state-level macroeconomic data, such as Gross Domestic Product (GDP), population, personal income, and house price index, I merge Call Reports data with macroeconomic data collected from the U.S. Census Bureau, the U.S. Department of the Treasury, the U.S. Bureau of Economic Analysis (BEA), and the Federal Housing Finance Agency (FHFA).

I also collect branch-level deposit data from Summary of Deposits surveys, provided by the Federal Deposit Insurance Corporation (FDIC), and state-level business loan creation data from DealScan.

At the state level, I exclude banks in Delaware and South Dakota from my sample because the unique presence of the credit card industry in these states affected their banking systems. My final sample consists of 201,853 bank-years in 1,127 state-years of data on 16,326 unique banks.

3.3.1 Bank Liquidity Creation

Berger and Bouwman (2009) provide four different liquidity creation measures depending on loan classification and off-balance sheet items. Because of data limitations,

---

[6] I consider a bank to be a thrift if it has residential real estate loans exceeding 50% of GTA, and I consider a bank to be a credit card bank if the bank has consumer loans exceeding 50% of GTA.

[7] I collect the quarterly and annual bank liquidity creation data from Christa Bouwman’s personal website (https://sites.google.com/a/tamu.edu/bouwman/data). The website provides four different bank liquidity creation measures, “cat fat,” “cat nonfat,” “mat fat,” and “mat nonfat”, for almost all commercial banks in the United States.

the bank liquidity creation measures can only classify loans based on category or maturity. Generally, regardless of their maturity, it is very difficult to dispose of business loans when banks require liquidity. On the other hand, it is easier to liquidate consumer loans and residential mortgage loans than business loans, regardless of their maturity. These circumstances demonstrate that loan categories would be more important factors than loan maturities in measuring asset-side bank liquidity creation.

Moreover, off-balance sheet liquidity creation accounts for approximately 40% of all liquidity creation. This suggests that I should take the off-balance sheet items into account to fully capture bank liquidity creation. Because of these fundamental characteristics of liquidity creation measures, I use a category-based bank liquidity creation measure that includes off-balance sheet activities ("cat fat"), as a proxy for bank liquidity creation.

Following Berger and Sedunov (2017), I construct state-level bank liquidity creation measure, relying on each bank's state deposit market shares as a proxy for weights on states where they operate branches. This is because branch-level financial data is not available, except branch-level deposits.

To estimate state-level "cat fat" measure, I firstly construct each bank's bank-state level market share using state-level deposit data from FDIC. By multiplying the bank-state level market share by each bank's liquidity creation measures, I can estimate bank-state level liquidity creation. For example, suppose Bank of America's total deposit in 2006 is $35 million and Florida branches have $10 million of deposit, South Carolina branches have $5 million of deposit, and Texas branches have $20 million of deposit. I can see that Bank of America's market share in Florida is 28.57% (= $10 million/$35 million). If the value of "cat fat" for Bank of America in 2006 is $100 million, then I can assume that Bank of America creates $28.57 million in Florida at that time. After calculating the bank-state level liquidity creation, I combine all bank-state level liquidity creation by state. Lastly, I normalize the aggregate state-level bank liquidity creation by state population.

3.3.2 Bank Competition

My key independent variables are proxies for bank competition. Previous studies suggest that bank deregulation facilitates bank competition and reallocates assets to more competitive banks. Following previous studies exploring U.S. interstate banking deregulation and interstate bank branching deregulation, I utilize the exogenous variations in state-level bank competition after the staggered interstate bank deregulation and interstate bank branching deregulation events in the U.S.

Interstate banking deregulation occurred primarily in the 1980s. It permits banks whose headquarters are in other states to acquire a state's incumbent banks. However, it does not allow banks to acquire or establish a branch in the deregulated state. Based on years when interstate banking was permitted, I construct an interstate bank deregulation variable (INTER), which is an indicator variable that takes the value of one from the year of deregulation onward and zero prior to the deregulation.

I also exploit the staggered interstate bank branching deregulation. The IBBEA was passed in 1994 and implemented in 1997 to allow interstate branching. However, the U.S. government gives states the authority to regulate interstate branching. State governments can either create or relax interstate bank branching restrictions.

As Johnson and Rice (2008) and Rice and Strahan (2010) state, interstate bank branching deregulation is more important than intra- and interstate bank deregulation for bank competition and credit supply. This is because loan contracts and deposit contracts are accomplished at the branch level. To construct an interstate branching deregulation index, I follow previous seminal papers, such as Johnson and Rice (2008), Rice and Strahan (2010), and Krishnan, Nandy, and Puri (2014).

The IBBEA allows state governments to erect barriers to entry. According to Johnson and Rice (2008) and Rice and Strahan (2010), and Krishnan, Nandy, and Puri (2014), there are five specific restrictions on interstate bank branching. The first restriction is the minimum age of the target banks. States can impose a minimum age of three or more years on target banks of interstate branch acquirers. The maximum age restriction is five years. The second restriction is de novo interstate branching. A state is more restricted if the state does not allow de novo interstate branching. The third restriction is the acquisition of individual branches. To weaken excessive external acquisitions, deregulated states can require an out-of-state bidder bank to acquire all branches of its target bank. A state is more regulated if the state does not allow individual branch acquisitions. The last restriction is a statewide deposit cap. The IBBEA mandates a maximum deposit concentration of 30%. However, state governments still have the authority to set a higher or lower entry barrier regarding deposit cap, which is the maximum amount of deposits that a single bank can hold. Thus, a state is more regulated if the state sets a deposit cap of less than 30%.

Krishnan, Nandy, and Puri (2014) add one more restriction to the index. The Krishnan, Nandy, and Puri Index (IBBEA) includes four restrictions, which are stated above, and adds the additional restriction of reciprocal requirement. This requirement means that interstate branching is allowed only if both the state, where an out-of-state bank wants to enter, and the home state of the out-of-state bank permit the same level of interstate branching.

Based on these restrictions, they construct the interstate bank branching deregulation index (IBBEA). The value of the IBBEA index increases in line with how relaxed a state's restrictions are. They add one point to the IBBEA if a state releases any barrier to entry. Thus, the maximum value of the IBBEA index with a reciprocal requirement is five, which indicates the states that are the most open to interstate bank branching. I mainly use the IBBEA index with the reciprocal requirement, and I use the IBBEA index without the reciprocal requirement as a robustness check. Thus, the IBBEA variable ranges from one (highly regulated) to five (deregulated) based on regulation conditions in a state, and it is zero prior to the implementation date. Using the bank deregulation events as exogenous shocks allows me to mitigate potential endogeneity concerns such as omitted variables and reverse causality. Methodology will be discussed in Section 3.4.

To examine bank-level analysis, I use the Lerner index, which is an individual measure of competition for each bank and each period, as a proxy for bank competition. The Lerner index is commonly used in recent studies of bank competition (e.g., Berger, Klapper, and Turk-Ariss 2009; Berger and Roman 2014).

Following the existing literature, I construct the Lerner index. The Lerner index i s defined as the difference between price and marginal cost, divided by price. In other w ords, it measures the market power of a bank to set a price above marginal cost. Thus, hi gh Lerner index values are associated with significant market power. I consider $Price_{it}$ as the price of GTA proxied by the ratio of total revenues to GTA for bank i at time t and MC_{it} as the marginal cost of total assets for bank i at time t.[8]

[3] To compute MC_{it} for each bank for each time period, I take the derivative from the following estimated translog cost function: $\ln(Cost_{it}) = \theta_0 + \theta_1 \ln GTA_{it} + \frac{\theta_2}{2} \ln GTA_{it}^2 + \sum_{k=1}^{3} \gamma_k \ln W_{k,it} + \sum_{k=1}^{3} \emptyset_k \ln GTA_{it} \ln W_{k,it} + \sum_{k=1}^{3} \sum_{j=1}^{3} \gamma_{kj} \ln W_{k,it} \ln W_{j,it} + \theta_3 Time_t + \mu_{it}$

The estimated coefficients of the cost function are then used to compute the marginal cost for GTA: $MC_{it} = \frac{Cost_{it}}{GTA_{it}} \left[\widehat{\theta_1} + \widehat{\theta_2} \ln GTA_{it} + \sum_{k=1}^{3} \widehat{\emptyset_k} \ln W_{k,it} \right]$. I provide the more detailed process for

$$Lerner_{it} = \frac{Price_{it} - MC_{it}}{Price_{it}}$$

Using the Lerner index as a proxy for bank competition, I examine the relationship between bank competition and bank liquidity creation at the bank level, but I cannot claim a causal relationship because of endogeneity concerns. To mitigate the endogeneity concerns, as with the state-level analysis, I utilize exogenous variations in bank competition throughout the U.S. bank deregulation events.

3.3.3 Control Variables

To investigate clear relationships between bank competition and bank liquidity creation, I include control variables that influence aggregate state-level liquidity created by banks. For state-level analysis, I control for local market macroeconomic conditions, including natural logarithm of state population, House Price Index (HPI), natural logarithm of personal income, GDP per capita, state deposit per capita, state equity per capita, number of potential borrowers, and number of competitors.

For bank-level analysis, I include a group of bank-level variables. I control for equity capital ratio, which is the ratio of equity to GTA. To control for bank risk, I include a Z-Score, which is the distance to default measured as the bank's return on assets plus the equity capital/GTA ratio divided by the standard deviation of the return on assets, and earnings volatility, which is measured as the standard deviation of the bank's return on assets over the previous twelve (or minimum of eight) quarters. I also control for a bank's multibank holding company (MBHC) status because MBHC banks could have much greater resources that could potentially affect bank liquidity creation strategies.

constructing the Lerner index in Internet Appendix B.

Furthermore, I control for a bank's merger and acquisition history because banks often substantially alter their lending behavior following mergers and acquisitions.

Departing from Berger and Bouwman (2009), I do not include bank size, market share, and a bank-level Herfindahl index as control variables in specifications using the Lerner index as a proxy for bank competition because these variables are strongly related to the Lerner index. However, I control for bank size when I use bank deregulation variables as proxies for bank competition. To control for macroeconomic conditions of local markets in bank-level analysis, I control for natural logarithm of state population, HPI, natural logarithm of personal income, and GDP per capita.

Finally, I include year fixed effects, firm fixed effects, state fixed effects, and state-year fixed effects in various bank-level specifications to control for time-specific effects, individual firm specific effects, state-specific effects, and state-level trends, respectively. I do not report results including state-fixed effects because state fixed effects are chiefly nested within bank fixed effects and the results are consistent with specifications, including bank fixed effects.

3.3.4 Models

To investigate whether bank competition is associated with bank liquidity creation, I estimate following equations:

$$\mathrm{State\ LC_{jt}} = \alpha_j + \alpha_t + \gamma \mathrm{Control_{jt-1}} + \delta \mathrm{Deregulation_{jt}} + \varepsilon_{jt} \quad (2)$$

where j indexes state, t indexes year, State LC_{jt} is the key dependent variable of interest, which is state-level liquidity creation variables, and $\mathrm{Deregulation}_{jt}$ is the key independent variable, which is staggered bank deregulation events, including interstate bank deregulation and interstate bank branching deregulation index. Control_{jt} is a set of state-level macroeconomic variables, and ε_{it} is an error term. I use the lagged values for control variables to mitigate a concern about reverse causality. I also include state fixed effects (α_j) and year fixed effects (α_t) to control for time-invariant unobserved characteristics of states and the time trend such as a set of macroeconomic condition, such as inflation, federal funds rate, and so on.

Using the staggered passage of bank deregulation to measure changes in competition, I perform a difference-in-differences analysis. This allows me to mitigate endogeneity concerns, including reverse causality and omitted variable problems.

States that create more liquidity may have less state-level competition, and state-level bank liquidity creation could affect the patterns of bank deregulation across states because regulators may implement policies based on poor liquidity creation within a state. Exploiting state-level regulatory changes could mitigate this issue. I can utilize variation in bank competition both over time and in the cross-section to identify the effect of bank deregulation events because states were deregulated at different times.

Another concern is an omitted variable problem in which unobservable variables that coincide with the bank deregulation events could result in changes in bank liquidity creation. The staggered characteristic of bank deregulation events across states can address the omitted variable bias because omitted variables that are not related to deregulation events would not demonstrate the same patterns, with multiple shocks that occur in different states at different times.

To examine bank-level relationships between bank competition and bank liquidity creation, I use both the fixed effects model and the difference-in-differences model. Please see Table 2 and Internet Appendix A for more detailed explanations of the models for bank-level analysis.

Panel A of Table 1 shows summary statistics for state-level variables. All financial variables are calculated in real 2006 dollars. Panels B and C of Table 1 report summary statistics for all sample banks, large banks, small banks, and the difference in summary statistics between large banks and small banks. I divide sample banks into three groups by size. I define a bank as a large bank if its gross total assets (GTA) exceed $3 billion. If a bank's GTA are between $1 billion and $3 billion, I define it as a medium-sized bank. The third sample, banks whose GTA are up to $1 billion, are defined as small banks. I have 16,326 unique sample banks for the sample period between 1984 and 2006. Among the sample banks, only 550 and 1,136, respectively, are categorized as large banks and medium-sized banks at least once. This represents only 10% of the total sample banks. This means that approximately 90% of the sample banks are defined as small banks.

From Panel C of Table 1, I also find that there are highly statistically significant differences between small banks and medium-sized/large banks for all liquidity creation behavior and bank characteristic variables. This suggests that there is substantial heterogeneity between small banks and medium-sized/large banks in terms of both liquidity creation behaviors and bank characteristics.

Table 3.1 Summary Statistics

This table contains state-level and bank-level summary statistics and contains summary statistics that compare small banks with medium/large banks. The sample comprises 16,326 unique commercial banks over the period 1984 to 2006. All financial values are measured in real 2006 dollars using the implicit GDP price deflator. Panel A shows state-level descriptive statistics. Liquidity creation measure is a category-based liquidity creation measure, including both on-balance sheet and off-balance sheet activities (“cat fat”). INTER is an indicator variable, which is equal to 1 from the year of interstate deregulation onward and 0 prior to the deregulation. IBBEA Index is Krishnan-Nandy-Puri interstate bank branching deregulation index. It ranges from one (highly regulated) to five (deregulated), and it is equal to zero prior to the deregulation. GDP is state-level gross domestic production. Personal Income is state-level personal income level. HPI is state-level housing price index. In Panel A, state-level variables with a “per capita” suffix are variables normalized by state population. Please see Appendix A for the detailed definition of the variables.

Panel A: Summary Statistics (State-level)

	N	Mean	SD
State-level Bank Deregulation Variables			
INTER	1,127	0.884	0.321
IBBEA (Reverse Rice and Strahan Index, 4 restrictions)	1,127	1.382	1.777
IBBEA (Krishnan-Nandy-Puri Index, 5 restrictions)	1,127	1.675	1.966
State Liquidity Creation Variables			
Liquidity Creation per Capita	1,127	8.143	5.540
Small Bank Liquidity Creation per Capita	1,127	1.356	1.107
Medium Bank Liquidity Creation per Capita	1,127	0.741	0.729
Large Bank Liquidity Creation per Capita	1,127	6.047	5.571
Small/Medium Bank Liquidity Creation per Capita	1,127	2.096	1.506
MSA Liquidity Creation per Capita	1,127	6.552	5.608
Non-MSA Liquidity Creation per Capita	1,127	1.592	2.026
Liquidity Creation by New Banks per Capita	1,127	0.294	0.904
Liquidity Creation by Existing Banks per Capita	1,127	7.850	5.454
Liquidity Creation by Home Banks per Capita	1,127	6.262	4.765
Liquidity Creation by Away Banks per Capita	1,127	1.881	3.457
Asset-side Liquidity Creation per Capita	1,127	0.669	1.579
Liability-side Liquidity Creation per Capita	1,127	3.968	1.827
Off-balance sheet Liquidity Creation per Capita	1,127	3.507	3.915
State Loan Creation Variables			
LN(State Loan Creation)	1,001	22.122	2.125
LN(State Loan Creation per capita)	1,001	7.017	1.545
LN(State Loan Creation per Borrowers)	1,001	17.742	1.458
LN(State Loan Creation per Competitors)	1,001	17.599	1.895
State-level Variables			
LN(Number of Competitors)	1,078	4.476	1.161
LN(Number of Borrowers)	1,078	4.295	1.337
LN(Population)	1,078	15.025	1.003
HPI	1,078	201.269	85.121
State-level Deposit per Capita	1,078	8.766	3.803
State-level Equity per Capita	1,078	1.654	0.994
GDP per Capita	1,078	28,344	12,930
Personal Income per Capita	1,078	23.216	7.573

Panel B: Summary Statistics (Bank-level)

Panel B presents bank-level descriptive statistics for the full sample, and Panel C presents univariate differences between small banks versus medium/large banks. Each bank is categorized by size based on its gross total assets (GTA). Gross total assets (GTA) is total assets + the allowance for loan and lease losses + the allocated transfer risk reserve (a reserve for certain foreign loans). A bank is classified as a large bank if its GTA are exceeding $3 billion, as a medium bank if its GTA are between $1 billion and $3 billion, and as a small bank if its GTA are below $1 billion. Liquidity creation measure is a category-based liquidity creation measure, including both on-balance sheet and off-balance sheet activities. Liquidity creation variables with a "GTA" suffix are liquidity creation measures normalized by GTA. Lerner Index is the observed price-cost margin divided by price. Equity Ratio is total equity capital divided by GTA. Bank Size is Natural log of GTA. Earnings Volatility is standard deviation of the bank's quarterly return on assets measured over the previous twelve quarters, multiplied by 100. ZSCORE is the bank's return on assets plus the equity capital/GTA ratio divided by the standard deviation of the return on assets. Multi-BHC is an indicator variable, which is equal to 1 if the bank has been part of a multibank holding company over the past three years. Acquisitions is an indicator variable, which is equal to 1 if the bank was acquired in the last three years. INTER is an indicator variable, which is equal to 1 from the year of interstate deregulation onward and 0 prior to the deregulation. IBBEA Index is Krishnan-Nandy-Puri interstate bank branching deregulation index. It ranges from one (highly regulated) to five (deregulated), and it is equal to zero prior to the deregulation.

	N	Mean	SD
Liquidity Creation Variables			
Liquidity Creation	201,440	264,188	4,591,513
Asset-side Liquidity Creation	201,440	28,288	740,957
Liability-side Liquidity Creation	201,440	116,638	1,582,129
Off-balance sheet Liquidity Creation	201,440	119,262	2,994,539
Liquidity Creation/GTA	201,440	0.196	0.180
Asset-side Liquidity Creation/GTA	201,440	-0.019	0.137
Liability-side Liquidity Creation/GTA	201,440	0.176	0.065
Off-balance sheet Liquidity Creation/GTA	201,440	0.038	0.060
Bank-level Variables			
Lerner Index	201,440	0.320	0.097
EQRAT	201,440	0.092	0.031
Bank Size	201,440	11.738	1.150
Earnings Volatility	201,375	0.004	0.004
ZSCORE	192,170	47.741	53.773
Multi-BHC	201,440	0.301	0.459
Acquisitions	201,440	0.036	0.188
State-level Bank Deregulation Variables			
INTER	201,440	0.832	0.374
IBBEA (Reverse Rice and Strahan Index, 4 restrictions)	201,440	0.913	1.470
IBBEA (Krishnan-Nandy-Puri Index, 5 restrictions)	201,440	1.165	1.675

Panel C: t-test (Small Banks vs. Large/Medium Banks)

	Small Banks			Large and Medium Banks			t-test	
	N	Mean	SD	N	Mean	SD	Difference	p-value
Liquidity Creation Variables								
Liquidity Creation	191,194	36,149	63,804	10,246	4,519,481	19,883,716	4,483,332	0.000
Asset-side Liquidity Creation	191,194	140	30,355	10,246	553,538	3,238,360	553,398	0.000
Liability-side Liquidity Creation	191,194	28,742	35,973	10,246	1,756,816	6,808,689	1,728,074	0.000
Off-balance sheet Liquidity Creation	191,194	7,267	20,967	10,246	2,209,127	13,103,651	2,201,860	0.000
Liquidity Creation/GTA	191,194	0.186	0.173	10,246	0.373	0.213	0.187	0.000
Asset-side Liquidity Creation/GTA	191,194	-0.022	0.137	10,246	0.039	0.121	0.061	0.000
Liability-side Liquidity Creation/GTA	191,194	0.174	0.064	10,246	0.212	0.067	0.038	0.000
Off-balance sheet Liquidity Creation/GTA	191,194	0.034	0.045	10,246	0.122	0.164	0.088	0.000
Bank-level Variables								
Lerner Index	191,194	0.322	0.096	10,246	0.276	0.096	-0.046	0.000
Equity Ratio	191,194	0.092	0.031	10,246	0.077	0.026	-0.015	0.000
Bank Size	191,194	11.561	0.842	10,246	15.039	1.129	3.478	0.000
Earnings Volatility	191,137	0.004	0.004	10,238	0.004	0.003	0.000	0.000
ZSCORE	182,131	47.905	54.013	10,039	44.772	49.125	-3.133	0.000
Multi-BHC	191,194	0.281	0.450	10,246	0.670	0.470	0.389	0.000
Acquisitions	191,194	0.026	0.158	10,246	0.241	0.428	0.215	0.000

3.4 Empirical Results

3.4.1 Relation between Competition and Liquidity Creation at the Bank level

This section describes the relationship between bank competition and bank liquidity creation. Using the Lerner index as a proxy for bank competition and the “cat fat” measure, which is scaled by gross total assets, as a proxy for bank-level liquidity creation, I investigate how bank-level strategy for liquidity creation is associated with the ex-ante extent of bank competition. My analysis includes controls for a wide range of variables that could affect bank liquidity creation, as mentioned in Section 3.3.

Columns 1 to 4 of Table 2 present ordinary least squares (OLS) estimates of the relationship between bank competition and bank liquidity creation. The competition variable in these columns is the Lerner index, and all independent variables, except multibank holding company status, are lagged. Columns 1 and 3 of Table 2 include both bank fixed effects and time fixed effects, and columns 2 and 4 include both bank fixed effects and state-year fixed effects that control for time-varying state-specific unobservables. Additionally, all specifications are estimated with robust standard errors, clustered by bank, to control for heteroskedasticity, as well as possible correlations between observations of the same bank in different years.

Using the Lerner index as a proxy for bank competition, I find a statistically and economically significant inverse relationship between bank competition and bank liquidity creation. Because a higher Lerner index value implies greater market power, banks with greater market power would create more liquidity in the market. The result remains significant even after I control for bank characteristics and state-level macroeconomic conditions. This shows that an increase of one standard deviation in the Lerner index is related to a 5.9% increase in predicted bank liquidity creation. To control for state-specific time trends such as regulatory changes, I include state-year fixed effects instead of year fixed effects in columns 2 and 4. The inverse relationship between bank competition and liquidity creation is still maintained.

Columns 5 and 6 of Table 2 examine the effect of interstate banking deregulation on bank liquidity creation using a difference-in-differences methodology. I find that, on average, exogenous variations in bank competition after interstate banking deregulation events do not significantly affect bank liquidity creation. This could be because of fixed costs to invest in deregulated states. Because interstate banking deregulation only allow banks to acquire or establish a charter, it requires much higher fixed costs to invest in deregulated states. Thus, only sizable banks are able to acquire and/or establish a charter in a state outside the bank's home state. On the other hand, small banks would not be able to compete with the sizable competitors. That is why these two effects could offset each other. In addition, existing large banks in the deregulated state could have the opportunity to invest in other deregulated states. This could also impact on the insignificant effects of interstate deregulation.

In contrast to Jiang, Levine, and Lin (2019), I utilize interstate bank branching deregulation to identify the variation in bank competition, as seen in columns 7 and 8. Because they only focus on interstate bank deregulation, their measure may not properly identify the effects of bank competition on liquidity creation after interstate bank branching deregulation. For example, small banks may not have sufficient resources to invest in deregulated states even if neighboring states implement interstate banking deregulation because interstate banking deregulation only allows banks to acquire or establish a charter. In this case, it could be possible that interstate bank competitive pressure facing commercial banks in the deregulated states might not be intense even if their distance-weighted interstate deregulation measure indicates that it is. After the implementation of interstate bank branching deregulation, the fixed cost to invest in deregulated states significantly decreases because banks can acquire or establish a branch in the deregulated states. Thus, examining interstate bank branching deregulation could explain different perspectives of the relationship between bank competition and bank liquidity creation.

Columns 7 and 8 report the results of fixed effects regressions, examining the effect of interstate branching deregulation on bank liquidity creation. The coefficient estimates of IBBEA are negative and significant at 5% on average. This finding suggests that an increase in banking competition due to bank branching deregulation leads to a decrease in bank liquidity creation. To be specific, based on the coefficient of IBBEA in column 8 of Table 2, states that are completely open to interstate branching generated a total of 2.6% less liquidity creation after interstate bank branching deregulation than states with the most restrictions on interstate branching after deregulation. The results are consistent with my previous results using the Lerner index and the results of Jiang, Levine, and Lin (2019).[9]

Understanding the relationship between bank competition and bank-level liquidity creation is interesting and important, but understanding the relationship between state-level bank competition and aggregate state-level bank liquidity creation would be much more important because government policies are generally established at the state level and regulators would put more stress on state-level performance than on bank-level performance after the implementation of government policies such as interstate banking

[9] However, the results from Table 2 do not explain what types of banks dominate this relationship and which component of bank liquidity creation is more correlated with bank competition. I present the findings for different categories of banks, such as bank size and bank liquidity components, in Internet Appendix A.

deregulation and interstate bank branching deregulation. In addition, the state-level analysis allows me to investigate whether the policies about bank competition led to effective bank liquidity creation.

In the next section, exploiting interstate bank deregulation and interstate bank branching deregulation, I examine whether changes in state-level bank competition following bank deregulation events are related to aggregate state-level bank liquidity creation.

Table 3.2 Relation between Competition and Liquidity Creation at the Bank level

$$BLC_{it} = \alpha_i + \alpha_t + \beta_0 + \beta_1 Lerner_{it-1} + \gamma_1 Control_{it-1} + \gamma_2 Macro\_Control_{jt-1} + \varepsilon_{ijt}$$

$$Liquidity_{it} = \alpha_i + \alpha_t + \delta Deregulation_{jt} + \gamma_1 Control_{it-1} + \gamma_2 Control_{jt-1} + \varepsilon_{ijt}$$

This table presents the estimation results that analyze the relation between bank competition and bank liquidity creation. The analysis is at bank-year level. The dependent variable is "cat fat", which is a category-based liquidity creation measure, including both on-balance sheet and off-balance sheet activities, normalized by GTA. The competition variable in Columns 1 – 4 is Lerner Index, which is the observed price-cost margin divided by price. In columns 5 and 6, the competition variable is interstate banking deregulation variable (INTER), which is equal to 1 from the year of interstate deregulation onward and 0 prior to the deregulation. In Columns 7 and 8, the competition variable is IBBEA Index, which is Krishnan-Nandy-Puri interstate bank branching deregulation index. It ranges from one (highly regulated) to five (deregulated), and it is equal to zero prior to the deregulation. The specifications in Column 1, 3, 5, 6, 7, and 8 include bank and year fixed effects. The specifications in Columns 2 and 4 include bank and state-year fixed effects. Macroeconomic variables include natural log of state population, GDP per capita, natural log of state personal income per capita, and house price index (HPI). Standard errors are adjusted for potential heteroskedasticity and for group correlation at bank level in Columns 1 – 4. Standard errors are clustered at state-level in Columns 5 – 8 to allow for an arbitrary serial correlation within state over time because the deregulation variables vary at the state level. Also, specifications in Columns 7 and 8 control for interstate bank deregulation (INTER) but do not include in the table. All independent variables except bank deregulation variables and MBHC are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

	(1) Lerner Index	(2) Lerner Index	(3) Lerner Index	(4) Lerner Index	(5) INTER	(6) INTER	(7) IBBEA	(8) IBBEA
Competition	0.093*	0.071*	0.141*	0.129**	0.004	0.013	-0.004**	-0.003**
	(0.05)	(0.04)	(0.07)	(0.06)	(0.01)	(0.01)	(0.00)	(0.00)
EQRAT			-0.788***	-0.827***		-0.664***		-0.662***
			(0.08)	(0.08)		(0.07)		(0.07)
Bank Size						0.014**		0.014**
						(0.01)		(0.01)
EARNVOL			-1.055*	-0.803		-1.284		-1.270
			(0.55)	(0.55)		(0.89)		(0.89)
ZSCORE			-0.000	-0.000***		-0.000		-0.000
			(0.00)	(0.00)		(0.00)		(0.00)
MBHC			0.019***	0.015***		0.020***		0.020***
			(0.00)	(0.00)		(0.00)		(0.00)
Acquisition			0.001	0.003*		-0.004		-0.004
			(0.00)	(0.00)		(0.00)		(0.00)
Constant	0.102***	0.295***	-0.230	0.193***	0.126***	-0.427	0.126***	-0.381
	(0.01)	(0.05)	(0.25)	(0.06)	(0.01)	(0.46)	(0.01)	(0.46)
Observations	182,606	182,606	174,404	174,404	201,853	174,404	201,853	174,404
Adjusted R-squared	0.789	0.806	0.803	0.814	0.770	0.802	0.770	0.802
Control Variables	No	No	Yes	Yes	No	Yes	No	Yes
Macroeconomic Variables	No	No	Yes	No	No	Yes	No	Yes
Fixed Effects	Firm, Year	Firm, State-Year	Firm, Year	Firm, State-Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
Cluster	Firm	Firm	Firm	Firm	State	State	State	State

3.4.2 Effects of Bank Deregulation on State-level Liquidity Creation

Regulators design policies to improve market systems. Bank deregulation policies are designed to invigorate local economies by stimulating depressed local capital markets. Bank-level results show that enhanced bank competition decreases bank liquidity creation. This suggests that bank deregulation may not lead to effective bank liquidity creation for local markets. However, results of the sub-sample analysis suggest that the reverse relationship between bank competition and liquidity creation is driven by small banks. Because of these heterogeneous relationships, it is extremely unclear whether enhanced bank competition through bank deregulation events is associated with aggregate state-level liquidity creation. Thus, in this section, I directly examine whether bank competition increases or decreases state-level bank liquidity creation.

Table 3 reports the results of regressions, examining the effects of bank deregulation on state-bank liquidity creation per capita. Panel A of Table 3 focuses on interstate banking deregulation, and Panel B focuses on interstate bank branching deregulation. Columns 1 and 2 of both panels present the base results, and columns 3 through 8 report the results for each liquidity component.

Surprisingly, I find that there is no statistically significant empirical evidence that both deregulation events affect state-level bank liquidity creation. The results are robust if I control for macroeconomic variables and state-level characteristics, such as number of competitors, number of borrowers, state equity per capita, and state deposit per capita.

Because bank deregulation stimulates bank competition and its objective is to enhance the financing condition of the market, this result is meaningful. The results suggest that interstate bank deregulation and interstate bank branching deregulation did not play an appropriate role in encouraging banks to create liquidity.

One possible explanation for this is that the policies did not take bank and market heterogeneity into consideration. Thus, in the following section, I examine the differences in the effects of two bank deregulation events depending on bank heterogeneity and market heterogeneity.

Table 3.3 Effects of Bank Deregulation on State-Level Liquidity Creation

This table presents the estimation results that analyze the effect of interstate bank deregulation and interstate bank branching deregulation on state-level bank liquidity creation. The analysis is at state-year level. The dependent variables are state-level "cat fat" measure normalized by state population (Columns 1 and 2), state-level asset-side liquidity creation normalized by state population (Columns 3 and 4), state-level liability-side liquidity creation normalized by state population (Columns 5 and 6), and state-level off-balance sheet liquidity creation normalized by state population (Columns 7 and 8). The bank deregulation variable in Panel A is INTER, which is equal to 1 from the year of interstate bank deregulation onward and 0 prior to the deregulation, and the bank deregulation variable in Panel B is IBBEA, which is Krishnan-Nandy-Puri interstate bank branching deregulation index. It ranges from one (highly regulated) to five (deregulated), and it is equal to zero prior to the deregulation. All specifications include state and year fixed effects. Control variables include state-level deposit per capita, state-level equity per capita, natural log of number of potential competitors, natural log of number of potential borrowers, natural log of state population, GDP per capita, natural log of state personal income per capita, and house price index (HPI). Standard errors are adjusted for potential heteroskedasticity and for group correlation at state level to allow for an arbitrary serial correlation within state over time because the deregulation variables vary at the state level. All control variables are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

Panel A: Interstate Bank Deregulation

	(1) State LC	(2) State LC	(3) State LC_A	(4) State LC_A	(5) State LC_L	(6) State LC_L	(7) State LC_O	(8) State LC_O
INTER	0.997	0.774	1.081**	0.650*	0.206	-0.175	-0.291	0.300
	(0.79)	(0.59)	(0.47)	(0.36)	(0.33)	(0.25)	(0.49)	(0.40)
Constant	4.329***	-106.242**	0.054	-46.680*	2.755***	28.399	1.519***	-87.961*
	(0.32)	(51.05)	(0.17)	(26.43)	(0.12)	(18.52)	(0.24)	(46.42)
Observations	1,127	1,078	1,127	1,078	1,127	1,078	1,127	1,078
Adjusted R-squared	0.790	0.838	0.282	0.500	0.747	0.839	0.766	0.823
Control Variables	No	Yes	No	Yes	No	Yes	No	Yes
Fixed Effects	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year

Panel B: Interstate Bank Branching Deregulation

	(1) State LC	(2) State LC	(3) State LC_A	(4) State LC_A	(5) State LC_L	(6) State LC_L	(7) State LC_O	(8) State LC_O
IBBEA	-0.288	-0.106	-0.283***	0.012	-0.170*	0.045	-0.113*	-0.033
	(0.18)	(0.16)	(0.10)	(0.08)	(0.09)	(0.08)	(0.06)	(0.05)
INTER		0.735		0.479		0.666*		-0.187
		(0.60)		(0.31)		(0.35)		(0.26)
Constant	4.491***	-103.538**	3.019***	-18.591	0.231	-47.816*	2.789***	29.225
	(0.28)	(51.28)	(0.20)	(28.59)	(0.23)	(26.96)	(0.13)	(18.83)
Observations	1,127	1,078	1,127	1,078	1,127	1,078	1,127	1,078
Adjusted R-squared	0.790	0.838	0.623	0.743	0.268	0.500	0.749	0.839
Control Variables	No	Yes	No	Yes	No	Yes	No	Yes
Fixed Effects	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year

3.4.3 The Heterogeneous Effects of Deregulation on Liquidity Creation

As I discussed above, interstate banking deregulation and interstate bank branching deregulation have different implications. Interstate banking deregulation could be more effective for large banks because it only allows banks to acquire and/or establish a charter rather than a branch. Because of this restriction, expected cost to enter the deregulated state are relatively high, suggesting that small banks may not be able to invest in the new market because of insufficient funds. Interstate bank branching deregulation lowers the fixed cost by allowing banks to acquire and/or establish branches in the deregulated states. With the lowered fixed cost, small banks could have more opportunities to invest in the deregulated states following interstate bank branching deregulation than interstate banking deregulation. Thus, I report the estimation using each event in each panel of the following tables.

In Columns 3 through 8 of Panel A of Table 3, I show that interstate bank deregulation increases only asset-side bank liquidity creation. I also find a negative relationship between interstate bank deregulation and liability-side liquidity creation and a positive relationship between interstate bank deregulation and off-balance sheet liquidity creation, but these relationships are statistically insignificant. These results show that banks operating in deregulated states are more likely to create liquidity through asset-side activities, such as illiquid loan creation, and replenish liquidity through liability-side activities, such as illiquid subordinated debt. In examining interstate bank branching deregulation, I find no statistically significant relationship between competition and liquidity creation, but the signs of coefficients on liquidity components demonstrate the opposite. The results suggest that the relationship between bank competition and bank liquidity creation varies in different liquidity creation components.

Berger and Sedunov (2017) find that small bank liquidity creation is more important than large bank liquidity creation in terms of per-dollar effects. This could be because small banks are more focused on small firm finance, which is more important to local market growth, than large banks are. In contrast to small-sized borrowers, large firms have more options for raising funds and would prefer large lenders because large banks have greater resources and much lower default risks than small banks. Thus, in Table 4, I examine whether bank deregulation events affect state-level small bank liquidity creation and large bank liquidity creation differently.

In Column 1 of Panel A of Table 4, I find positive and statistically significant evidence that interstate banking deregulation affects state-level small bank liquidity creation, but the significance disappears after controlling for state-level macroeconomic variables and state characteristics. Columns 3 and 4 of Panel A show positive and statistically significant coefficient estimates, suggesting that interstate banking deregulation increases state-level bank liquidity created by medium-sized banks. The result is robust when controlling for state-level variables. In Columns 5 and 6, I find no significant relationship between bank competition and state-level bank liquidity created by large banks.

There are several possible explanations for these results. Large banks may not have much incentive to create more liquidity in the market if they are dominant players because they can enjoy monopolistic rents, such as lower deposit rates and higher loan rates. This could explain why there is no significant relationship between bank competition and state-level large-bank liquidity creation.

As bank competition increases, small banks increase bank liquidity creation to maintain their relationship banking because the number of new players in the market following interstate banking deregulation might be relatively small due to high fixed costs, but it could also be possible that small banks decrease liquidity creation to avoid default risks in the competitive market. These opposing incentives could offset each other, and this could explain the insignificant relationship between bank competition and state-level bank liquidity created by small banks.

Medium-sized banks have more resources than small banks, so they are capable of entering the deregulated markets with high fixed costs. In addition, medium-sized banks can compete with new players by creating more liquidity in the market. It is also possible that large banks acquire medium banks in the deregulated states or establish medium-sized bank charters in the deregulated states. In this case, the data captures these banks' liquidity creation as state-level medium-sized bank liquidity creation in the deregulated states. That is why I find a positive and significant effect of bank competition on bank liquidity created by medium-sized banks.

Panel B of Table 4 reports the results for interstate bank branching deregulation. Interstate bank branching deregulation is much more important for bank liquidity creation than other bank deregulation events that occurred in the 1970s and 1980s. Because loan and deposit decisions, which are major drivers of on-balance sheet liquidity creation, are generally made at branch level, interstate bank branching deregulation would have more direct and significant effects on bank liquidity creation.

Columns 2 and 4 of Panel B of Table 4 show that coefficients on the IBBEA variable are negative and statistically significant, which suggests that interstate bank branching deregulation decreases bank liquidity created by small and medium-sized banks at the state-level. On the other hand, columns 5 and 6 of Panel B show that there is no significant relationship between IBBEA and state-level large bank liquidity creation.

As Petersen and Rajan (1994, 1995) suggest, in highly competitive markets, there would be many banks to compete, and borrowers would have many different alternatives for finance. This would nullify the value of existing lenders' private information about borrowers because new lenders can verify the private information. Thus, in this case, banks lose their information advantage. In the post-IBBEA period, small and medium-sized banks are more likely to lose their information advantage because smaller banks tend to be involved in relationship banking with local borrowers. Specifically, different from interstate banking deregulation, interstate bank branching deregulation lowers fixed costs to enter the new markets, so it could lead to significant increase in number of competitive banks, which have sufficient resources to acquire the private information about the lenders, in the deregulated markets. Thus, small and medium banks reduce their liquidity creation within a state. Another possible explanation is that competitive newcomers may be able to offer unbeatable interest rates and deposit rates to borrowers, that have long relationship with local lenders, because they have enough funding sources to dominate the market. These could explain the negative and statistically significant relationship between IBBEA and small and medium-sized bank liquidity creation at the state level.

Because large banks create more liquidity in terms of dollar values and small banks are reluctant to create liquidity in the competitive market, the results support the view that large banks enjoy monopolistic rents if they are dominant players. The results are robust if I use alternative measures of interstate bank branching deregulation. The findings suggest that interstate bank branching deregulation results in even worse local market liquidity conditions because small bank liquidity creation is a crucial channel for local market growth (e.g., Berger and Sedunov, 2017).

The conclusion of the analysis by bank size is that interstate banking deregulation and interstate bank branching deregulation appear to affect state-level bank liquidity creation differently based on the size of banks that create liquidity in the market. This could explain the insignificant effect of bank competition on state-level bank liquidity creation, as shown in Table 3. The results are also consistent with my expectation that two bank deregulation events have different effects and implications.

Table 3.4 Effects of Bank Deregulation on State-Level Liquidity Creation by Size

This table presents the estimation results that analyze the effect of interstate bank deregulation and interstate bank branching deregulation on state-level bank liquidity created by different sized banks. The analysis is at state-year level. The dependent variables are state-level bank liquidity created by small banks, normalized by state population (Columns 1 and 2), state-level bank liquidity created by medium banks, normalized by state population (Columns 3 and 4), and state-level bank liquidity created by large banks, normalized by state population (Columns 5 and 6). The bank deregulation variable in Panel A is INTER, which is equal to 1 from the year of interstate bank deregulation onward and 0 prior to the deregulation, and the bank deregulation variable in Panel B is IBBEA, which is Krishnan-Nandy-Puri interstate bank branching deregulation index. It ranges from one (highly regulated) to five (deregulated), and it is equal to zero prior to the deregulation. All specifications include state and year fixed effects. Control variables include state-level deposit per capita, state-level equity per capita, natural log of number of potential competitors, natural log of number of potential borrowers, natural log of state population, GDP per capita, natural log of state personal income per capita, and house price index (HPI). Standard errors are adjusted for potential heteroskedasticity and for group correlation at state level to allow for an arbitrary serial correlation within state over time because the deregulation variables vary at the state level. All control variables are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

Panel A: Interstate Bank Deregulation

	(1) State Small LC	(2) State Small LC	(3) State Medium LC	(4) State Medium LC	(5) State Large LC	(6) State Large LC
INTER	0.792***	0.272	0.509***	0.423***	-0.305	0.080
	(0.29)	(0.19)	(0.17)	(0.14)	(0.51)	(0.45)
Constant	0.912***	19.188	0.534***	-14.958	2.883***	-110.473**
	(0.12)	(11.81)	(0.10)	(10.33)	(0.30)	(46.80)
Observations	1,127	1,078	1,127	1,078	1,127	1,078
Adjusted R-squared	0.678	0.817	0.335	0.405	0.814	0.851
Control Variables	No	Yes	No	Yes	No	Yes
Fixed Effects	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year

Panel B: Interstate Bank Branching Deregulation

	(1) State Small LC	(2) State Small LC	(3) State Medium LC	(4) State Medium LC	(5) State Large LC	(6) State Large LC
IBBEA	-0.258***	-0.103***	-0.136***	-0.045*	0.106	0.042
	(0.05)	(0.04)	(0.05)	(0.03)	(0.19)	(0.16)
INTER		0.234		0.406***		0.095
		(0.18)		(0.14)		(0.45)
Constant	1.041***	21.813*	0.617***	-13.805	2.833***	-111.545**
	(0.09)	(11.69)	(0.09)	(10.22)	(0.27)	(47.27)
Observations	1,127	1,078	1,127	1,078	1,127	1,078
Adjusted R-squared	0.692	0.822	0.336	0.406	0.814	0.850
Control Variables	No	Yes	No	Yes	No	Yes
State FE	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year

To provide further evidence that the effect of bank competition on state-level bank liquidity creation is heterogeneous and depends on bank or market characteristics, I examine whether state-level bank liquidity created by MSA branches and liquidity created by non-MSA branches react differently to enhanced bank competition. Panel A of Table 5 reports the results, examining the effect of interstate banking deregulation on state-level bank liquidity creation. In columns 1 and 2, I find no significant effect on state-level bank liquidity created by bank branches that locate in MSA areas. On the other hand, I find a positive and statistically significant effect on state-level bank liquidity created by bank branches that locate in non-MSA areas. This makes sense because non-MSA areas are relatively less competitive than MSA areas and bank branches in non-MSA areas may still have an information advantage over new potential lenders even after interstate banking deregulation. It is also plausible that out-of-state banks would have an incentive to acquire non-MSA bank branches in the deregulated states because of relatively higher concentrations than MSA bank branches. In this case, the acquired banks could still have an information advantage, so they would want to keep it by creating more liquidity in the relatively concentrated local market.

Panel B of Table 5 reports results for IBBEA. In columns 1 and 2, I examine whether IBBEA relates to state-level MSA liquidity creation and find no significant results. However, in columns 3 and 4, I examine whether IBBEA is associated with state-level liquidity created by bank branches located in non-MSA areas and find a negative and significant relationship. From the perspective of private information access, branches in non-MSA areas would lose the information advantage because there would be many more potential new competitors in the case of IBBEA than the case of interstate banking deregulation due to the much lower fixed cost for entering deregulated states. In this situation, these banks may have an incentive to keep the liquidity within a bank to avoid default risk. This could explain the negative relationship between IBBEA and state-level non-MSA liquidity creation.

I conclude that the results in Table 5 suggest that there is heterogeneous effect of bank competition on state-level liquidity creation depending on a bank's location, supporting the main finding of my paper. In addition, the results suggest two bank deregulation events have heterogeneous effects and implications.

Table 3.5 Effects of Bank Deregulation on State-level MSA Liquidity Creation

This table presents the estimation results that analyze the effect of interstate bank deregulation and interstate bank branching deregulation on state-level bank liquidity created by bank branches located in metropolitan statistical areas (MSAs) and non-MSA areas. The analysis is at state-year level. The dependent variables are state-level bank liquidity created by MSA bank branches, normalized by state population (Columns 1 and 2) and state-level bank liquidity created by non-MSA bank branches, normalized by state population (Columns 3 and 4). The bank deregulation variable in Panel A is INTER, which is equal to 1 from the year of interstate bank deregulation onward and 0 prior to the deregulation, and the bank deregulation variable in Panel B is IBBEA, which is Krishnan-Nandy-Puri interstate bank branching deregulation index. It ranges from one (highly regulated) to five (deregulated), and it is equal to zero prior to the deregulation. All specifications include state and year fixed effects. Control variables include state-level deposit per capita, state-level equity per capita, natural log of number of potential competitors, natural log of number of potential borrowers, natural log of state population, GDP per capita, natural log of state personal income per capita, and house price index (HPI). Standard errors are adjusted for potential heteroskedasticity and for group correlation at state level to allow for an arbitrary serial correlation within state over time because the deregulation variables vary at the state level. All control variables are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

Panel A: Interstate Bank Deregulation

	(1) State MSA LC	(2) State MSA LC	(3) State Non-MSA LC	(4) State Non-MSA LC
INTER	-0.073	0.031	1.070***	0.743***
	(0.56)	(0.54)	(0.39)	(0.26)
Constant	3.599***	-137.862**	0.730***	31.619
	(0.27)	(54.15)	(0.22)	(23.71)
Observations	1,127	1,078	1,127	1,078
Adjusted R-squared	0.788	0.820	0.401	0.493
Control Variables	No	Yes	No	Yes
Fixed Effects	State, Year	State, Year	State, Year	State, Year

Panel B: Interstate Bank Branching Deregulation

	(1) State MSA LC	(2) State MSA LC	(3) State Non-MSA LC	(4) State Non-MSA LC
IBBEA	-0.026	0.043	-0.262**	-0.149
	(0.15)	(0.11)	(0.10)	(0.09)
INTER		0.046		0.689***
		(0.55)		(0.25)
Constant	3.587***	-138.951**	0.905***	35.413
	(0.24)	(54.89)	(0.18)	(22.87)
Observations	1,127	1,078	1,127	1,078
Adjusted R-squared	0.788	0.820	0.399	0.496
Control Variables	No	Yes	No	Yes
State FE	State, Year	State, Year	State, Year	State, Year

In Table 6, I analyze the effect of bank competition on state-level bank liquidity created by banks whose headquarters are in-state and by banks whose headquarters are out-of-state, respectively. In columns 1 and 2 of Panel A of Table 6, I find that enhanced bank competition following interstate bank deregulation increases state bank liquidity created by banks whose headquarters are located in deregulated states. In columns 3 and 4, I demonstrate whether interstate banking deregulation affects state-level bank liquidity created by banks whose headquarters are located outside the deregulated states. In column 3, I find a negative and statistically significant result, but the significance disappears after controlling for state characteristics and state-level macroeconomic indicators, as shown in column 4. These results suggest that in-state banks and out-of-state banks respond differently to changes in competition following interstate banking deregulation.

In Panel B of Table 6, I analyze the relationship between enhanced bank competition through IBBEA and state-level bank liquidity created by in-state banks and out-of-state banks. Columns 2 and 4 show that the coefficients on IBBEA are negative and statistically insignificant, even after controlling for state characteristics and macroeconomic conditions.

I conclude that the evidence is weak for a relationship between changes in bank competition induced by regulatory events, and state-level bank liquidity varies depending on whether banks are headquartered in the deregulated state or in another state. Moreover, consistent evidence exists that two interstate bank deregulatory events play different roles in the market.

The results of state-level analyses provide an important policy implication. The objective of bank deregulation is to encourage local economies, and a crucial channel through which banks can contribute to the economic growth of local markets is bank liquidity creation. Although previous literature finds that the relaxation of restrictions positively affects economic growth in local markets, my results suggest that the positive effects might not be driven by bank-oriented activity, which is bank liquidity creation. Thus, the policy implication of the state-level results is that government regulations regarding bank competition should consider banks' and markets' heterogeneity, and one stubborn policy for all heterogeneous banks and markets would not be effective in maximizing local market growth.

Table 3.6 Effects of Bank Deregulation on State-level Liquidity Creation by Home Status

This table presents the estimation results that analyze the effect of interstate bank deregulation and interstate bank branching deregulation on state-level bank liquidity created by banks whose headquarters are located in the state and banks whose headquarters are located outside the state. The analysis is at state-year level. The dependent variables are state-level bank liquidity created by home banks, normalized by state population (Columns 1 and 2) and state-level bank liquidity created by away banks, normalized by state population (Columns 3 and 4). The bank deregulation variable in Panel A is INTER, which is equal to 1 from the year of interstate bank deregulation onward and 0 prior to the deregulation, and the bank deregulation variable in Panel B is IBBEA, which is Krishnan-Nandy-Puri interstate bank branching deregulation index. It ranges from one (highly regulated) to five (deregulated), and it is equal to zero prior to the deregulation. All specifications include state and year fixed effects. Control variables include state-level deposit per capita, state-level equity per capita, natural log of number of potential competitors, natural log of number of potential borrowers, natural log of state population, GDP per capita, natural log of state personal income per capita, and house price index (HPI). Standard errors are adjusted for potential heteroskedasticity and for group correlation at state level to allow for an arbitrary serial correlation within state over time because the deregulation variables vary at the state level. All control variables are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

Panel A: Interstate Bank Deregulation

	(1) State Home LC	(2) State Home LC	(3) State Away LC	(4) State Away LC
INTER	2.440***	1.067*	-1.443***	-0.293
	(0.84)	(0.61)	(0.45)	(0.32)
Constant	4.086***	-70.286	0.242	-35.957
	(0.36)	(56.38)	(0.21)	(30.00)
Observations	1,127	1,078	1,127	1,078
Adjusted R-squared	0.606	0.730	0.586	0.762
Control Variables	No	Yes	No	Yes
Fixed Effects	State, Year	State, Year	State, Year	State, Year

Panel B: Interstate Bank Branching Deregulation

	(1) State Home LC	(2) State Home LC	(3) State Away LC	(4) State Away LC
IBBEA	-0.670*	-0.104	0.382	-0.002
	(0.37)	(0.21)	(0.35)	(0.15)
INTER		1.029*		-0.294
		(0.58)		(0.32)
Constant	4.485***	-67.643	0.006	-35.895
	(0.35)	(55.25)	(0.23)	(29.67)
Observations	1,127	1,078	1,127	1,078
Adjusted R-squared	0.607	0.730	0.586	0.762
Control Variables	No	Yes	No	Yes
State FE	State, Year	State, Year	State, Year	State, Year

3.4.4 Additional Robustness Tests

Results in state-level analyses support the implication that a policy to encourage bank competition would be more efficient if it applies to banks depending on heterogenous factors such as bank size and bank market share, and to markets depending on heterogenous factors such as market demand and supply-side competition status prior to the implementation of the policy.

However, I still have a concern about reverse causality. Previous studies suggest that government policies, including bank deregulation, could be driven by external factors such as political connections. This suggests that my results could be driven by reverse causality even though I identify changes in bank competition through staggered bank deregulation events. To mitigate this issue, following Bertrand and Mullainathan (2003), I examine the dynamic effects of interstate bank deregulation and interstate bank branching deregulation on state-level bank liquidity creation.

To check the pre-existing trends in bank liquidity creation, I construct four variables for each bank deregulation event. For interstate banking deregulation, I construct four dummy variables based on different time periods, such as all years up to and including two years prior to deregulation, one year prior to deregulation, one year after deregulation, and two or more years after deregulation. For interstate bank branching deregulation, I also deconstruct the state-level components of IBBEA into four dummy variables. To identify changes in the IBBEA index, I sum the four component variables for each period. Finally, I construct Before2+, Before1, After1, and After2+, corresponding to the four time periods.

In this context, the deregulation year is the reference year. The coefficient estimates of Before2+ and Before1 indicate whether there is any relationship between bank liquidity creation and bank deregulation events before bank deregulation events.

The coefficient estimates of After2+ and After1 are important because their significance and magnitude may indicate whether there is any relationship between bank deregulation and bank liquidity creation after implementation of bank deregulation events. If I find a positive and significant relationship in post-deregulation periods, it could suggest that government policies lead to effective liquidity creation after one or two years from the effective year.

In columns 1 and 2 of Table 7, I report the results for interstate bank deregulation. In column 1, I find a negative and slightly significant relationship between Before1 and interstate banking deregulation, but the significance disappears after controlling for state-macroeconomic variables and state-level characteristics. In columns 3 and 4, I present the results for interstate bank branching deregulation, and I find no significant relations for four variables.

The insignificant results suggest that state-level liquidity creation shows no significant change between pre- and post-bank deregulatory periods. This indicates that trends in state-level bank liquidity creation do not cause bank deregulation events and mitigates concerns about reverse causality.

Table 3.7 Dynamics of Liquidity Creation surrounding Deregulatory Events

This table presents the estimation results that analyze the dynamics of liquidity creation surrounding deregulation events. The analysis is at state-year level. The dependent variable is state-level “cat fat”, normalized by state population. The bank deregulation variable in Columns 1 and 2 is INTER, which is equal to 1 from the year of interstate bank deregulation onward and 0 prior to the deregulation, and the bank deregulation variable in Columns 3 and 4 is IBBEA, which is equal to 1 from the year of interstate bank branching deregulation onward and 0 prior to the deregulation. Before2+ is an indicator variable that takes the value of 1×(Δ Deregulation Variable) from the beginning of the window up to two years prior to a regulatory change and zero otherwise. Before1 is an indicator variable that takes the value of 1×(Δ Deregulation Variable) the year prior to a regulatory change and zero otherwise. After2+ is an indicator variable that takes the value of 1×(Δ Deregulation Variable) in the second year following a deregulation until the end of the window and zero otherwise. After1 is an indicator variable that takes the value of 1×(Δ Deregulation Variable) in the year following a regulatory change and zero otherwise. All specifications include state and year fixed effects. Control variables include state-level deposit per capita, state-level equity per capita, natural log of number of potential competitors, natural log of number of potential borrowers, natural log of state population, GDP per capita, natural log of state personal income per capita, and house price index (HPI). Standard errors are adjusted for potential heteroskedasticity and for group correlation at state level to allow for an arbitrary serial correlation within state over time because the deregulation variables vary at the state level. All control variables are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

VARIABLES	(1) INTER	(2) INTER	(3) IBBEA	(4) IBBEA
Before 2+	-0.515	-0.902	0.472	0.477
	(0.67)	(0.57)	(0.82)	(0.76)
Before 1	-0.352*	-0.280	0.127	0.110
	(0.21)	(0.24)	(0.46)	(0.50)
After 1	0.277	0.061	-0.207	-0.015
	(0.23)	(0.22)	(0.14)	(0.14)
After 2+	1.210	0.386	-0.237	-0.030
	(0.77)	(0.63)	(0.19)	(0.18)
Constant	4.803***	-108.775**	4.019***	-106.332**
	(0.43)	(50.39)	(0.87)	(52.17)
Observations	1,127	1,078	1,127	1,078
Adjusted R-squared	0.791	0.838	0.789	0.837
Control Variables	No	Yes	No	Yes
Fixed Effects	State, Year	State, Year	State, Year	State, Year

Another concern about state-level analysis is the definition of state-level bank liquidity creation. Because there are no available branch-level financial and accounting data apart from branch-level deposit data, I only rely on deposit market share to calculate weights for each state when I construct state-level liquidity creation. Deposit market share would be closely related to a bank's concentration on the market, but potential exists for measurement error. To mitigate this concern, I use DealScan data to construct a partial measure of state-level bank liquidity creation. DealScan data provides information about a borrower's location and total loan amount, so I use the information to calculate more accurate state-level liquidity creation weights. Even though loan creation is a part of bank liquidity creation, which is a part of asset-side liquidity creation, using DealScan data allows me to identify correct weights for each state in which a bank operates. Table 8 shows that the results of state-level analyses using DealScan data are consistent with previous results using state-level bank liquidity creation relying on deposit market shares. In columns 1 and 2 of Panels A and B, I find that there is no significant effect of bank competition on state-level loan creation, which is proxied by a natural logarithm of state-level deal amount. As a robustness check, I use alternative state-level loan creation measures, such as state loan creation per capita, state loan creation per in-state borrower, and state loan creation per in-state competitor, in the remaining columns. The results are robust to the alternative measures. They suggest that the main state-level liquidity creation measures in this paper are valid, and that the results are also credible.

Furthermore, I use a different comprehensive liquidity creation measure, "mat fat," instead of "cat fat." The only difference between the "cat fat" and "mat fat" measures is the way they classify loans. The "cat fat" measure classifies loans by category, while the "mat fat" measure classifies loans by maturity. It will be ideal if I can consider both category and maturity when I classify the loans. Unfortunately, lack of available data does not allow us to consider both measures. Because category-based classification captures loan-specific characteristics, Berger and Bouwman (2009) suggest that the "cat fat" measure is the most comprehensive measure of bank liquidity creation among their four liquidity creation measures. However, maturity-based classification would be essential when I compare the same kinds of loans. Thus, there is a possibility that maturity-based classification has merit for evaluating loan-side liquidity creation. For this reason, I run the identical tests using the "mat fat" measure as a robustness check. The results are still consistent, but I do not report the results because of space limitations.

Table 3.8 Effects of Bank Deregulation on Local Loan Creation

This table presents the estimation results that analyze the effect of interstate bank deregulation and interstate bank branching deregulation on state-level loan creation. Panel A shows the results that examine the effect of interstate bank deregulation on state-level loan creation, and Panel B shows the results that examine the effect of interstate bank branching deregulation on state-level loan creation. The analysis is at state-year level. Because of significant missing observations before 1987, the sample period for the analysis in this table is from 1987 – 2006. The dependent variables are state-level aggregate loan creation measures. The dependent variables are natural log of state-level loan creation in Columns 1 and 2, natural log of state-level loan creation normalized by state population in Columns 3 and 4, natural log of state-level loan creation normalized by number of borrowers within a state in Columns 5 and 6, and natural log of state-level loan creation normalized by number of competitors within a state in Columns 7 and 8, respectively. The bank deregulation variable in Panel A is INTER, which is equal to 1 from the year of interstate bank deregulation onward and 0 prior to the deregulation, and the bank deregulation variable in Panel B is IBBEA, which is equal to 1 from the year of interstate bank deregulation onward and 0 prior to the deregulation All specifications include state and year fixed effects. Control variables include state-level deposit per capita, state-level equity per capita, natural log of number of potential competitors, natural log of number of potential borrowers, natural log of state population, GDP per capita, natural log of state personal income per capita, and house price index (HPI). Standard errors are adjusted for potential heteroskedasticity and for group correlation at state level to allow for an arbitrary serial correlation within state over time because the deregulation variables vary at the state level. All control variables are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

Panel A: Interstate Bank Deregulation

	(1) ln(Loan Creation)	(2) ln(Loan Creation)	(3) ln(State Loan per	(4) ln(State Loan per	(5) ln(State Loan per	(6) ln(State Loan per	(7) ln(State Loan per	(8) ln(State Loan per
INTER	0.275	0.188	0.227	0.116	0.243	0.171	-0.220	0.024
	(0.42)	(0.43)	(0.41)	(0.42)	(0.41)	(0.43)	(0.42)	(0.44)
Constant	20.104***	16.123	5.186***	14.057	15.914***	16.246	16.056***	20.274*
	(0.42)	(11.47)	(0.40)	(10.81)	(0.42)	(11.26)	(0.43)	(11.45)
Observations	951	951	951	951	951	951	951	951
Adjusted R^2	0.872	0.873	0.752	0.754	0.655	0.655	0.811	0.820
Control	No	Yes	No	Yes	No	Yes	No	Yes
Fixed Effects	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year

Panel B: Interstate Bank Branching Deregulation

	(1) ln(Loan Creation)	(2) ln(Loan Creation)	(3) ln(State Loan per capita)	(4) ln(State Loan per capita)	(5) ln(State Loan per borrowers)	(6) ln(State Loan per borrowers)	(7) ln(State Loan per competitors)	(8) ln(State Loan per competitors)
IBBEA	-0.062*	-0.039	-0.046	-0.036	-0.051	-0.039	0.024	-0.033
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
INTER		0.181		0.109		0.163		0.018
		(0.43)		(0.42)		(0.43)		(0.43)
Constant	20.326***	17.128	5.369***	14.999	16.110***	17.257	15.877***	21.127*
	(0.19)	(11.88)	(0.18)	(11.19)	(0.18)	(11.67)	(0.19)	(11.83)
Observations	951	951	951	951	951	951	951	951
Adjusted R^2	0.872	0.873	0.753	0.754	0.656	0.655	0.811	0.820
Control	No	Yes	No	Yes	No	Yes	No	Yes
Fixed Effects	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year

3.5 Conclusion

The role of banks as liquidity creators is crucial for local market conditions and economic growth. However, the determinants of bank liquidity creation are understudied. While a large corpus of literature suggests that bank competition affects local market economic growth, it is unclear whether bank liquidity creation is a major economic driver of the effects of bank competition on economic outputs. The empirical evidence presented in this paper suggests that the effects of bank competition on economic growth may not originate from bank liquidity creation.

Surprisingly, state-level analysis shows that, on average, interstate and interstate bank branching deregulation events do not significantly affect state-level bank liquidity creation. This suggests that, overall, government policy regarding bank competition did not lead to effective bank liquidity creation in local markets.

Additional analysis examines whether changes in bank competition following bank deregulation events are associated with state-level bank liquidity created by heterogeneous banks or banks in heterogeneous markets. I find that the effects of bank competition on state-level bank liquidity creation vary depending on policy regarding bank competition, bank size, geographic area, and banks' home-state status.

The divergent results make sense because interstate bank deregulation, which only allows banks to acquire/establish a charter rather than a branch, requires potential new players in deregulated states to pay a much higher fixed cost. On the other hand, interstate bank branching deregulation allows banks to acquire/establish a branch, thus involving a much lower fixed cost when the potential players enter the deregulated markets. This suggests that two deregulation events are fundamentally different and that affected groups would be different as well.

More importantly, these results suggest that the policy, that is applied to all heterogeneous banks and markets in the same way, does not fit all. It highlights the role of proper regulation to encourage depressed credit market.

3.6 Appendix

This appendix presents variable definitions, additional bank-level analysis tables, and a detailed definition of bank-level competition variable, which is Lerner Index, to accompany the paper "Does Bank Competition Increase Bank Liquidity Creation? A State-level Perspective."

Appendix A. Variable Definition

State-level Bank Deregulation Variables	Definition	Source
INTER	An indicator variable that is equal to one from the year of interstate banking deregulation onward, and zero prior to interstate banking deregulation	Black and Strahan (2002)
IBBEA	Interstate Bank Branching deregulation index, which is equal to one for the state with the most restrictive interstate branching regulations as of the effective date, and increases by one for each restriction that is relaxed by a state. The index takes a value of zero in all years prior to the effective date	Rice and Strahan (2010) Krishnan, Nandy, and Puri (2015)
State Liquidity Creation Variables		
Liquidity Creation per Capita	Total liquidity creation of all banks in the state, normalized by the state's population	Berger and Bouwman (2009)
Small Bank Liquidity Creation per Capita	Total liquidity creation of banks in the state with less or equal to $1 billion in gross total assets, normalized by the state's population	Berger and Bouwman (2009)
Medium Bank Liquidity Creation per Capita	Total liquidity creation of banks in the state with less or equal to $3 billion and greater than $1 billion in gross total assets, normalized by the state's population	Berger and Bouwman (2009)
Large Bank Liquidity Creation per Capita	Total liquidity creation of banks in the state with greater than $3 billion in gross total assets, normalized by the state's population	Berger and Bouwman (2009)
Small/Medium Liquidity Creation per Capita	Total liquidity creation of banks in the state with less or equal to $3 billion in gross total assets, normalized by the state's population	Berger and Bouwman (2009)
MSA Liquidity Creation per Capita	Total liquidity creation of all banks in the state that operate in metropolitan statistical areas (MSAs), normalized by the state's population	Berger and Bouwman (2009)
Non-MSA Liquidity Creation per Capita	Total liquidity creation of all banks in the state that operate in non-metropolitan statistical areas (MSAs), normalized by the state's population	Berger and Bouwman (2009)
Liquidity Creation by Home Banks per Capita	Total liquidity creation of all banks in the state whose headquarters are located in the state, normalized by the state's population	Berger and Bouwman (2009)
Liquidity Creation by Away Banks per Capita	Total liquidity creation of all banks in the state whose headquarters are located in the out-of-state, normalized by the state's population	Berger and Bouwman (2009)
Asset-side Liquidity Creation per Capita	Total asset-side liquidity creation of all banks in the state, normalized by the state's population	Berger and Bouwman (2009)
Liability-side Liquidity Creation per Capita	Total liability-side creation of all banks in the state, normalized by the state's population	Berger and Bouwman (2009)
Off-balance sheet Liquidity Creation per Capita	Total off-balance sheet liquidity creation of all banks in the state, normalized by the state's population	Berger and Bouwman (2009)

State Loan Creation Variables		
LN(State Loan Creation)	LN(1+Total loans borrowed by all firms in the state)	DealScan
LN(State Loan Creation per capita)	Total loans borrowed by all borrowers in the state, normalized by the state's population	DealScan
LN(State Loan Creation per Borrowers)	Total loans borrowed by all borrowers in the state, normalized by total number of potential borrowers in the state	DealScan
LN(State Loan Creation per Competitors)	Total loans borrowed by all borrowers in the state, normalized by total number of potential lenders in the state	DealScan
State-level Variables		
LN(Number of Competitors)	LN(1+Total number of potential borrowers in the state)	Call Report
LN(Number of Borrowers)	LN(1+Total number of potential lenders in the state)	Compustat
LN(Population)	LN(1+The state's population)	US Census
HPI	House price index	Federal Housing Finance Agency (FHFA)
State-level Deposit per Capita	Total bank deposit in the state, normalized by the state's population	Call Report
State-level Equity per Capita	Total bank book equity in the state, normalized by the state's population	Call Report
GDP per Capita	State GDP of the state, normalized by the state's population	Bureau of Economic Analysis (BEA) US Census
Personal Income per Capita	State personal income of the state, normalized by the state's population	Bureau of Economic Analysis (BEA) US Census

Appendix B. Additional Bank-level Analysis

Table 3.1B consists of two panels. Panel A presents bank-level summary statistics, and Panel B presents t-test between small banks and large/medium banks.

Table 3.2B presents regressions of Lerner Index on bank liquidity creation. I find reverse relation between bank competition and bank liquidity creation at the bank level.

Table 3.3B reports sub-sample analysis examining the relation between bank competition and liquidity creation by bank size. Empirical results show that the reverse relation between bank competition and bank liquidity creation is driven by small banks. This suggests that small banks tend to keep more liquidity within a bank in the competitive market because small banks do not have sufficient resources to compete with larger banks and want to avoid potential default risk.

Table 3.4B reports sub-sample analysis examining the relation between bank competition and liquidity creation by liquidity creation components. The results show that the reverse relation is driven by asset-side liquidity creation and off-balance sheet liquidity creation.

Table 3.5B and 3.6B examine whether bank competition affects bank liquidity creation and whether the effect of bank competition on liquidity creation is different by bank size. Exploiting interstate banking deregulation, I find no statistically significant results. The passage of the interstate banking deregulation only allows banks to acquire and establish a charter in the deregulated states, so it requires high fixed costs to enter the new market. This means that only large banks would have incentive to expand their businesses in the deregulated states, and small banks may not have enough funds to either acquire or establish the charter. The results suggest that interstate banking deregulation might not be effective to encourage bank liquidity creation.

Table 3.7B and 3.8B examine whether interstate bank branching deregulation affects bank liquidity creation and whether the effect of bank competition on liquidity creation is different by bank size. Consistent with the results in Table 3.2B, I find the negative effect of bank competition on bank liquidity creation on average. However, sub-sample analysis shows different perspectives of bank deregulation. Different from interstate banking deregulation, interstation bank branching deregulation allowed banks to either acquire or establish a branch. This means that it requires much lower fixed costs to enter the new market than interstate banking deregulation. This could explain why small banks create more liquidity than large and medium banks and why large banks create less liquidity than small and medium banks. Small banks may want to create more liquidity to keep their relationship with local borrowers, and large banks might want to create less liquidity to enjoy monopolistic rents because they are more likely to be dominant players in the market.

Table 3.1B Summary Statistics

This table contains summary statistics for all sample banks and contains summary statistics that compare small banks with medium/large banks. The sample comprises 16,367 unique commercial banks over the period 1984 to 2006. Panel A presents bank -level descriptive statistics for the full sample. Panel B presents univariate differences between small banks versus medium/large banks. Each bank is categorized by size based on its gross total assets (GTA). Gross total assets (GTA) is total assets + the allowance for loan and lease losses + the allocated transfer risk reserve (a reserve for certain foreign loans). A bank is classified as a large bank if its GTA are exceeding $3 billion, as a medium bank if its GTA are between $1 billion and $3 billion, and as a small bank if its GTA are below $1 billion. Panel C shows state-level descriptive statistics. All financial values are measured in real 2007 dollars using the implicit GDP price deflator. The table reports number of observations, sample means, and standard deviations. For liquidity creation measures, catfat is a category-based liquidity creation measure, including both on-balance sheet and off-balance sheet activities. catnonfat is a category-based liquidity creation measure, including only on-balance sheet activities. Liquidity creation variables with a "/GTA" suffix are liquidity creation measures normalized by GTA. Lerner Index is the observed price-cost margin divided by price. Equity Ratio is total equity capital divided by GTA. Bank Size is Natural log of GTA. Earnings Volatility is standard deviation of the bank's quarterly return on assets measured over the previous twelve quarters, multiplied by 100. ZSCORE is the bank's return on assets plus the equity capital/GTA ratio divided by the standard deviation of the return on assets. Multi-BHC is an indicator variable, which is equal to 1 if the bank has been part of a multibank holding company over the past three years. Acquisitions is an indicator variable, which is equal to 1 if the bank was acquired in the last three years. INTER is an indicator variable, which is equal to 1 from the year of interstate deregulation onward and 0 prior to the deregulation. KNP5 Index is Krishnan-Nandy-Puri index of interstate banking deregulation. It ranges from one (highly regulated) to five (deregulated) based on regulation changes in a state.

Panel A: Summary Statistics (Bank-level)

	N	Mean	SD
Liquidity Creation Variables			
Liquidity Creation	201,440	264,188	4,591,513
Asset-side Liquidity Creation	201,440	28,288	740,957
Liability-side Liquidity Creation	201,440	116,638	1,582,129
Off-balance sheet Liquidity Creation	201,440	119,262	2,994,539
Liquidity Creation/GTA	201,440	0.196	0.180
Asset-side Liquidity Creation/GTA	201,440	-0.019	0.137
Liability-side Liquidity Creation/GTA	201,440	0.176	0.065
Off-balance sheet Liquidity Creation/GTA	201,440	0.038	0.060
Bank-level Variables			
Lerner Index	201,440	0.320	0.097
EQRAT	201,440	0.092	0.031
Bank Size	201,440	11.738	1.150
Earnings Volatility	201,375	0.004	0.004
ZSCORE	192,170	47.741	53.773
Multi-BHC	201,440	0.301	0.459
Acquisitions	201,440	0.036	0.188
State-level Bank Deregulation Variables			
INTER	201,440	0.832	0.374
IBBEA (Krishnan-Nandy-Puri Index, 5 restrictions)	201,440	1.165	1.675
IBBEA (Reverse Rice and Strahan Index, 4 restrictions)	201,440	0.913	1.471

Panel B: t-test (Small Banks vs. Large/Medium Banks)

	Small Banks			Large and Medium Banks			t-test	
	N	Mean	SD	N	Mean	SD	Difference	p-value
Liquidity Creation Variables								
Liquidity Creation	191,194	36,149	63,804	10,246	4,519,481	19,883,716	4,483,332	0.000
Asset-side Liquidity Creation	191,194	140	30,355	10,246	553,538	3,238,360	553,398	0.000
Liability-side Liquidity Creation	191,194	28,742	35,973	10,246	1,756,816	6,808,689	1,728,074	0.000
Off-balance sheet Liquidity Creation	191,194	7,267	20,967	10,246	2,209,127	13,103,651	2,201,860	0.000
Liquidity Creation/GTA	191,194	0.186	0.173	10,246	0.373	0.213	0.187	0.000
Asset-side Liquidity Creation/GTA	191,194	-0.022	0.137	10,246	0.039	0.121	0.061	0.000
Liability-side Liquidity Creation/GTA	191,194	0.174	0.064	10,246	0.212	0.067	0.038	0.000
Off-balance sheet Liquidity Creation/GTA	191,194	0.034	0.045	10,246	0.122	0.164	0.088	0.000
Bank-level Variables								
Lerner Index	191,194	0.322	0.096	10,246	0.276	0.096	-0.046	0.000
Equity Ratio	191,194	0.092	0.031	10,246	0.077	0.026	-0.015	0.000
Bank Size	191,194	11.561	0.842	10,246	15.039	1.129	3.478	0.000
Earnings Volatility	191,137	0.004	0.004	10,238	0.004	0.003	0.000	0.000
ZSCORE	182,131	47.905	54.013	10,039	44.772	49.125	-3.133	0.000
Multi-BHC	191,194	0.281	0.450	10,246	0.670	0.470	0.389	0.000
Acquisitions	191,194	0.026	0.158	10,246	0.241	0.428	0.215	0.000

Table 3.2B Relationship between Bank Competition and Bank Liquidity Creation

This table contains OLS panel regressions that examine the relation between bank competition and bank liquidity creation. The analysis is at bank-year level. The dependent variable is catfat, which is a category-based liquidity creation measure, including both on-balance sheet and off-balance sheet activities, normalized by GTA. The independent variable is Lerner Index, which is the observed price-cost margin divided by price. The specifications in Column 1 and 3 include bank and year fixed effects. The specifications in Columns 2 and 4 include bank and state-year fixed effects. Standard errors are adjusted for potential heteroskedasticity and for group correlation at firm level. All independent variables are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

	(1)	(2)	(3)	(4)
Lerner Index	0.044***	0.033***	0.068***	0.070***
	(0.01)	(0.01)	(0.02)	(0.02)
EQRAT			-0.750***	-0.785***
			(0.04)	(0.04)
EARNVOL			-0.474**	-0.136
			(0.22)	(0.22)
ZSCORE			-0.000	-0.000***
			(0.00)	(0.00)
MBHC			0.020***	0.017***
			(0.00)	(0.00)
Acquisition			0.000	0.002
			(0.00)	(0.00)
Constant	0.115***	0.307***	-0.335	0.196***
	(0.00)	(0.05)	(0.24)	(0.05)
Observations	182,259	182,259	174,094	174,094
Adjusted R-squared	0.792	0.805	0.801	0.810
Control Variables	No	No	Yes	Yes
Macroeconomic Variables	No	No	Yes	No
Fixed Effects	Bank, Year	Bank, State-Year	Bank, Year	Bank, State-Year

Table 3.3B Relationship between Bank Competition and Bank Liquidity Creation: Sub-sample analysis by bank size

This table contains OLS panel regressions that examine the relation between bank competition and bank liquidity creation in small, medium, and large banks. A bank is classified as a large bank if its GTA are exceeding $3 billion, as a medium bank if its GTA are between $1 billion and $3 billion, and as a small bank if its GTA are below $1 billion. The analysis is at bank-year level. The dependent variable is catfat, which is a category-based liquidity creation measure, including both on-balance sheet and off-balance sheet activities, normalized by GTA. The independent variable is Lerner Index, which is the observed price-cost margin divided by price. The specifications in Column 1, 3, and 5 include bank and year fixed effects. The specifications in Columns 2, 4, and 6 include bank and state-year fixed effects. Standard errors are adjusted for potential heteroskedasticity and for group correlation at firm level. All independent variables are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

	(1) Small Bank	(2) Small Bank	(3) Medium Bank	(4) Medium Bank	(5) Large Bank	(6) Large Bank
Lerner Index	0.067***	0.068***	0.078	0.072	0.093	0.084
	(0.02)	(0.02)	(0.11)	(0.08)	(0.11)	(0.08)
EQRAT	-0.769***	-0.804***	-0.299	-0.466	0.060	-0.332
	(0.04)	(0.04)	(0.39)	(0.37)	(0.29)	(0.39)
EARNVOL	-0.308*	0.002	-0.740	-0.426	-3.704*	-3.840**
	(0.18)	(0.18)	(1.42)	(1.25)	(1.89)	(1.59)
ZSCORE	-0.000	-0.000***	0.000	0.000	0.000*	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MBHC	0.022***	0.018***	-0.008	-0.007	-0.002	0.000
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)
Acquisition	0.002	0.004**	0.004	0.008*	-0.003	-0.003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Constant	-0.199	0.323***	-1.630	0.497***	0.497	0.543***
	(0.27)	(0.03)	(1.26)	(0.04)	(0.81)	(0.05)
Observations	164,739	164,739	5,388	5,388	3,967	3,967
Adjusted R-squared	0.805	0.814	0.711	0.766	0.674	0.743
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Macro Variables	Yes	No	Yes	No	Yes	No
Fixed Effects	Bank, Year	Bank, State-Year	Bank, Year	Bank, State-Year	Bank, Year	Bank, State-Year

Table 3.4B Relationship between Bank Competition and Bank Liquidity Creation: Sub-sample analysis by liquidity creation components

This table contains OLS panel regressions that examine the relation between bank competition and components of bank liquidity creation. The analysis is at bank-year level. The dependent variable in Columns 1 – 4 is asset-side liquidity creation normalized by GTA. The dependent variable in Columns 5 – 8 is liability-side liquidity creation normalized by GTA. The dependent variable in Columns 9 – 12 is off-the-balance sheet-side liquidity creation normalized by GTA. The independent variable is Lerner Index, which is the observed price-cost margin divided by price. The specifications in Column 1, 3, 5, 7, 9, and 11 include bank and year fixed effects. The specifications in Columns 2, 4, 6, 8, 10, and 12 include bank and state-year fixed effects. Standard errors are adjusted for potential heteroskedasticity and for group correlation at firm level. All independent variables are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

	(1)	(2)	(3)	(4)	(5)	(6)
	Asset-side liquidity creation	Asset-side liquidity creation	Liability-side liquidity creation	Liability-side liquidity creation	Off-balance sheet liquidity creation ("fat")	Off-balance sheet liquidity creation ("fat")
Lerner Index	0.041***	0.054***	0.005	-0.003	0.022**	0.019*
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
EQRAT	-0.269***	-0.317***	-0.440***	-0.424***	-0.041*	-0.044*
	(0.03)	(0.03)	(0.01)	(0.01)	(0.02)	(0.02)
EARNVOL	-0.399**	-0.093	-0.009	0.017	-0.066	-0.060
	(0.16)	(0.16)	(0.06)	(0.06)	(0.16)	(0.17)
ZSCORE	-0.000	-0.000***	0.000***	0.000**	-0.000***	-0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MBHC	0.020***	0.016***	-0.003***	-0.002***	0.003***	0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Acquisition	0.003**	0.004***	-0.003***	-0.002***	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-0.405*	-0.047	0.096	0.181***	-0.026	0.062***
	(0.22)	(0.05)	(0.06)	(0.02)	(0.06)	(0.02)
Observations	174,094	174,094	174,094	174,094	174,094	174,094
Adjusted R-squared	0.764	0.778	0.807	0.821	0.633	0.638
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic Variables	Yes	No	Yes	No	Yes	No
Fixed Effects	Bank, Year	Bank, State-Year	Bank, Year	Bank, State-Year	Bank, Year	Bank, State-Year

Table 3.5B Effects of Interstate Bank Deregulation on Bank Liquidity Creation

This table presents the estimation results that analyze the effect bank competition on bank liquidity creation. The analysis is at bank-year level. The dependent variable in Column 1 is catfat, which is a category-based liquidity creation measure, including both on-balance sheet and off-balance sheet activities, normalized by GTA. The dependent variables in Columns 2, 3, and 4 are asset-side liquidity creation normalized by GTA, liability-side liquidity creation normalized by GTA, and off-the-balance sheet-side liquidity creation normalized by GTA, respectively. The key independent variable is INTER, which is equal to 1 from the year of interstate deregulation onward and 0 prior to the deregulation. All specifications include bank and year fixed effects. Standard errors are adjusted for potential heteroskedasticity and for group correlation at state level. Different from the previous specifications using Lerner Index as a proxy for bank competition, all specifications in this table control for bank size and cluster by state-level to allow for an arbitrary serial correlation within state over time because the deregulation variables vary at the state level. All independent variables are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

	(1) CATFAT	(2) CATFAT	(3) Asset-side	(4) Asset-side	(5) Liability-side	(6) Liability-side	(7) Off-balance	(8) Off-balance
INTER	0.003	0.010	-0.000	0.008	0.003	0.000	-0.000	0.002
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
EQRAT		-0.672***		-0.189***		-0.487***		0.004
		(0.07)		(0.06)		(0.01)		(0.02)
Size		0.011**		0.018***		-0.018***		0.011***
		(0.01)		(0.00)		(0.00)		(0.00)
EARNVOL		-0.518		-0.337		-0.151		-0.030
		(0.33)		(0.24)		(0.10)		(0.16)
ZSCORE		-0.000		-0.000		0.000**		-0.000***
		(0.00)		(0.00)		(0.00)		(0.00)
MBHC		0.021***		0.020***		-0.003***		0.004***
		(0.00)		(0.00)		(0.00)		(0.00)
Acquisition		-0.003		-0.003		0.002**		-0.003**
		(0.00)		(0.00)		(0.00)		(0.00)
Constant	0.125***	-0.479	-0.050***	-0.540	0.162***	0.145	0.013***	-0.083
	(0.01)	(0.49)	(0.01)	(0.46)	(0.00)	(0.16)	(0.00)	(0.08)
Observations	201,440	174,094	201,440	174,094	201,440	174,094	201,440	174,094
Adjusted R-squared	0.776	0.801	0.734	0.765	0.770	0.813	0.664	0.636
Control Variables	No	Yes	No	Yes	No	Yes	No	Yes
Macroeconomic	No	Yes	No	Yes	No	Yes	No	Yes
Fixed Effects	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year

Table 3.6B Effects of Interstate Bank Deregulation on Bank Liquidity Creation: Sub-sample analysis by bank size

This table presents the estimation results that analyze the effect bank competition on bank liquidity creation in small, medium, and large banks. A bank is classified as a large bank if its GTA are exceeding $3 billion, as a medium bank if its GTA are between $1 billion and $3 billion, and as a small bank if its GTA are below $1 billion. The analysis is at bank-year level. The dependent variable is catfat, which is a category-based liquidity creation measure, including both on-balance sheet and off-balance sheet activities, normalized by GTA. The key independent variable is INTER, which is equal to 1 from the year of interstate deregulation onward and 0 prior to the deregulation. All specifications include bank and year fixed effects. Standard errors are adjusted for potential heteroskedasticity and for group correlation at state level. Different from the previous specifications using Lerner Index as a proxy for bank competition, all specifications in this table control for bank size and cluster by state-level to allow for an arbitrary serial correlation within state over time because the deregulation variables vary at the state level. All independent variables are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

	(1) Small Bank	(2) Small Bank	(3) Medium Bank	(4) Medium Bank	(5) Large Bank	(6) Large Bank
INTER	0.002	0.010	0.001	0.013	0.008	-0.004
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
EQRAT		-0.675***		-0.279		0.095
		(0.07)		(0.36)		(0.24)
Size		0.015**		0.017		-0.013
		(0.01)		(0.01)		(0.02)
EARNVOL		-0.316		-0.894		-4.004**
		(0.29)		(1.61)		(1.99)
ZSCORE		-0.000		0.000		0.000**
		(0.00)		(0.00)		(0.00)
MBHC		0.022***		-0.008		-0.002
		(0.00)		(0.01)		(0.01)
Acquisition		-0.002		0.000		-0.001
		(0.00)		(0.00)		(0.01)
Constant	0.118***	-0.351	0.219***	-1.935	0.318***	0.763
	(0.01)	(0.50)	(0.02)	(1.35)	(0.01)	(0.78)
Observations	191,194	164,739	5,916	5,388	4,330	3,967
Adjusted R-squared	0.777	0.805	0.749	0.711	0.681	0.674
Control Variables	No	Yes	No	Yes	No	Yes
Macroeconomic Variables	No	Yes	No	Yes	No	Yes
Fixed Effects	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year

Table 3.7B Effects of Interstate Branching Deregulation on Bank Liquidity Creation

This table presents the estimation results that analyze the effect interstate bank branching deregulation on bank liquidity creation. The analysis is at bank-year level. The dependent variable is catfat, which is a category-based liquidity creation measure, including both on-balance sheet and off-balance sheet activities, normalized by GTA. The key independent variable is IBBEA Index, which ranges from one (highly regulated) to five (deregulated) based on regulation changes in a state. INTER is equal to 1 from the year of interstate deregulation onward and 0 prior to the deregulation. All specifications include bank and year fixed effects. Standard errors are adjusted for potential heteroskedasticity and for group correlation at state level. Different from the previous specifications using Lerner Index as a proxy for bank competition, all specifications in this table control for bank size and cluster by state-level to allow for an arbitrary serial correlation within state over time because the deregulation variables vary at the state level. All independent variables are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

	(1) CATFAT	(2) CATFAT	(3) Asset-side	(4) Asset-side	(5) Liability-side	(6) Liability-side	(7) Off-balance	(8) Off-balance
IBBEA	-0.004**	-0.003*	-0.003**	-0.002	-0.001	-0.001	-0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
INTER		0.009		0.007		0.000		0.002
		(0.01)		(0.01)		(0.00)		(0.00)
EQRAT		-0.670***		-0.187***		-0.487***		0.005
		(0.07)		(0.06)		(0.01)		(0.02)
Size		0.012**		0.018***		-0.018***		0.011***
		(0.01)		(0.00)		(0.00)		(0.00)
EARNVOL		-0.504		-0.327		-0.149		-0.028
		(0.32)		(0.24)		(0.10)		(0.16)
ZSCORE		-0.000		-0.000		0.000**		-0.000***
		(0.00)		(0.00)		(0.00)		(0.00)
MBHC		0.021***		0.020***		-0.003***		0.004***
		(0.00)		(0.00)		(0.00)		(0.00)
Acquisition		-0.003		-0.003		0.002**		-0.003**
		(0.00)		(0.00)		(0.00)		(0.00)
Constant	0.126***	-0.432	-0.050***	-0.508	0.162***	0.153	0.013***	-0.077
	(0.01)	(0.49)	(0.01)	(0.46)	(0.00)	(0.16)	(0.00)	(0.08)
Observations	201,440	174,094	201,440	174,094	201,440	174,094	201,440	174,094
Adjusted R-squared	0.776	0.802	0.734	0.765	0.770	0.813	0.664	0.636
Control Variables	No	Yes	No	Yes	No	Yes	No	Yes
Macroeconomic Variables	No	Yes	No	Yes	No	Yes	No	Yes
Fixed Effects	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year

Table 3.8B Effects of Interstate Branching Deregulation on Liquidity Creation: Sub-sample analysis by bank size

This table presents the estimation results that analyze the effect interstate bank branching deregulation on bank liquidity creation in small, medium, and large banks. A bank is classified as a large bank if its GTA are exceeding $3 billion, as a medium bank if its GTA are between $1 billion and $3 billion, and as a small bank if its GTA are below $1 billion. The analysis is at bank-year level. The dependent variable is catfat, which is a category-based liquidity creation measure, including both on-balance sheet and off-balance sheet activities, normalized by GTA. The key independent variable is IBBEA Index, which ranges from one (highly regulated) to five (deregulated) based on regulation changes in a state. INTER is equal to 1 from the year of interstate deregulation onward and 0 prior to the deregulation. All specifications include bank and year fixed effects. Standard errors are adjusted for potential heteroskedasticity and for group correlation at state level. Different from the previous specifications using Lerner Index as a proxy for bank competition, all specifications in this table control for bank size and cluster by state-level to allow for an arbitrary serial correlation within state over time because the deregulation variables vary at the state level. All independent variables are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

	(1) Small	(2) Small	(3) Medium	(4) Medium	(5) Large	(6) Large	(7) Small	(8) Small	(9) Medium	(10) Medium	(11) Large	(12) Large
IBBEA	-0.004**	-0.003	-0.005	-0.003	-0.008	-0.006	-0.010***	-0.007***	-0.004**	-0.003*	-0.004**	-0.003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Small Bank							-0.021**	-0.003				
							(0.01)	(0.01)				
Small X IBBEA							0.006***	0.005**				
							(0.00)	(0.00)				
Medium Bank									0.011	0.004		
									(0.01)	(0.01)		
Medium X IBBEA									-0.003	-0.002		
									(0.00)	(0.00)		
Large Bank											0.021*	-0.002
											(0.01)	(0.01)
Large X IBBEA											-0.008***	-0.007**
											(0.00)	(0.00)
Constant	0.118***	-0.315	0.219***	-1.882	0.319***	0.906	0.146***	-0.424	0.125***	-0.430	0.125***	-0.428
	(0.01)	(0.50)	(0.02)	(1.30)	(0.01)	(0.83)	(0.01)	(0.49)	(0.01)	(0.49)	(0.01)	(0.49)
Observations	191,194	164,739	5,916	5,388	4,330	3,967	201,440	174,094	201,440	174,094	201,440	174,094
Adjusted R-squared	0.777	0.805	0.749	0.711	0.681	0.675	0.776	0.802	0.776	0.802	0.776	0.802
Control Variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Macroeconomic	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Fixed Effects	Bank,	Bank,	Bank,	Bank,	Bank,	Bank,	Bank,	Bank,	Bank,	Bank,	Bank,	Bank,

.

Appendix C. Lerner Index

Following the methodological approach of Berger, Klapper, and Turk-Ariss (2009) and Berger and Roman (2014), I consider $Price_{it}$ as the price of GTA proxied by the ratio of total revenues to GTA for bank i at time t and MC_{it} as the marginal cost of total assets fo r a bank i at time t. To compute MC_{it} for each bank for each time period, I take the derivative from the following estimated translog cost function:

$$Lerner_{it} = \frac{Price_{it} - MC_{it}}{Price_{it}}$$

$$\ln\left(Cost_{it}\right) = \theta_0 + \theta_1 \ln GTA_{it} + \frac{\theta_2}{2} \ln GTA_{it}^2 + \sum_{k=1}^{3} \gamma_k \ln W_{k,it}$$
$$+ \sum_{k=1}^{3} \emptyset_k \ln GTA_{it} \ln W_{k,it} + \sum_{k=1}^{3} \sum_{j=1}^{3} \gamma_{kj} \ln W_{k,it} \ln W_{j,it} + \theta_3 Time_t + \mu_{it}$$

where i represents banks, t represents time in quarters, $Cost_{it}$ is total operating plus financial costs, GTA_{it} is gross total assets, $W_{k,it}$ represents input prices, $W_{1,it}$ is the ratio of personnel expenses to GTA, which is proxy for input price of labor, $W_{2,it}$ is the ratio of interest expenses to total deposits and money market funding, which is proxy for input price of all funds, $W_{3,it}$ is the ratio of other operating and administrative expenses to GTA, which is proxy for input price of fixed capital, and $Time_t$ is a vector of time fixed effects. The estimated coefficients of the cost function are then used to compute the marginal cost for GTA:

$$MC_{it} = \frac{Cost_{it}}{GTA_{it}} \left[\widehat{\theta_1} + \widehat{\theta_2} \ln GTA_{it} + \sum_{k=1}^{3} \widehat{\emptyset_k} \ln W_{k,it} \right]$$

Chapter 4:

CEO Inside Debt and

Bank Liquidity Creation

4.1 Introduction

The recent financial crisis highlights the importance of corporate governance and regulation. Executive compensation is an issue of great importance to financial regulators. In 2010, the Dodd-Frank Wall Street Reform and Consumer Protection Act introduced a new "say on pay" provision. This provision allows shareholders to vote on executive compensation. The US Treasury Department also lobbied for tighter restrictions on CEO incentive compensation for banks who received funds through the Troubled Asset Relief Program (TARP).

Interest in debt-based compensation heightened in 2007 following the disclosure reform of the US Securities and Exchange Commission; this reform required firms to disclose their pensions and deferred compensation. As Jensen and Meckling (1976) propose a mechanism that mitigates the conflicts of agency between debtholders and agents, Chief Executive Officer (CEO) inside debt compensation plays an important role in alleviating the transfer of wealth from debtholders to shareholders by ensuring the conservative management of companies (e.g., Sundaram and Yermack 2007; Chava, Kumar, and Warga 2010; Cassell, Huang, Sanchez, and Stuart 2012; Anantharaman, Fang, and Gong 2014; Phan 2014; Srivastav, Armitage, and Hagendorff 2014; Bennett, Guntay, and Unal 2015; van Bekkum 2016).

Focusing on the banking industry, van Bekkum (2016) documents that CEOs with higher inside debt holdings decrease bank-specific risk and systemic risk. Van Bekkum's results suggest that regulators could mitigate their concerns about bank failure and the associated negative externalities for the economy by imposing higher requirements for inside debt compensation. Van Bekkum also finds that CEOs with higher inside debt holdings increase conservative banking activity. However, the author does not show empirical analysis to examine the effects of inside debt holdings on traditional banking activities such as lending and deposit-taking.

In this paper, I examine whether debt-like compensation for CEOs of banks is associated with bank liquidity creation. Bank liquidity creation is a crucial bank-side activity that affects both the local market economy and bank value. Past empirical literature on bank liquidity creation demonstrates that it is positively related to both bank value and economic outputs (e.g., Berger and Bouwman 2009; Berger and Sedunov 2017). Thus, it is important to investigate whether higher CEO inside debt holdings result in more conservative strategies of bank liquidity creation. These strategies are related to poor bank value and poor capital market on a local scale.

High liquidity creation ensures that more liquid funds are available on the market. For example, banks can create high liquidity on the market when they create illiquid assets (i.e., business loans) by using liquid liabilities (i.e., transaction deposits). This means that high bank liquidity creation is an even riskier strategy than high loan creation. In addition, high bank liquidity creation can give rise to financial crises, and high levels of bank liquidity creation could be precursors to future financial crises (e.g., Berger and Bouwman 2017). Because of the link between high liquidity creation and potential financial crises, CEOs with high personal leverage are incentivized to manage banks more carefully. A high proportion of debt-based compensation means they may be reluctant to take excessive risks, even though riskier projects have the potential to be more profitable than safer projects. CEOs typically do not want to take on risky projects at the expense of their debt-like compensation. Thus, I hypothesize that banks with CEOs who possess high inside debt holdings create less bank liquidity.

Using a sample of 119 banks listed in the United States from 2006 to 2016, I examine whether CEO inside debt holdings are related to bank liquidity creation. I find that inside debt holdings of bank CEOs are negatively related to bank liquidity creation, which is consistent with the hypothesis presented above. However, I find no significant results as to whether risk-taking incentives and pay-performance sensitivity play important roles in promoting bank liquidity creation. The results suggest that inside debt compensation discourages CEOs from implementing risky strategies of bank liquidity creation, even though these strategies would be beneficial to market participants. CEOs are also discouraged from implementing the high liquidity creation strategies despite the motivation that debt-like compensation provides them in pursuing more traditional banking activities.

By deconstructing the components of bank liquidity creation, I find that the negative relationship is driven by off-balance sheet liquidity creation. Berger and Bouwman (2009) prove that large banks create higher fractions of liquidity through off-balance sheet activities than small and medium-sized banks. They also prove that all banks, regardless of their size, create significant portions of their liquidity through off-balance sheet activities. This posits that bank size is an important factor in the relationship between inside debt holdings and bank liquidity creation. Thus, in this paper, I also examine whether there are heterogenous relations between CEO inside debt holdings and bank liquidity creation, conditional on bank size. I find that the results are driven by large banks. This implies that if regulators wish to encourage bank liquidity creation, they should motivate the CEOs of large banks by imposing restrictions on their compensation structures; large banks occupy roughly 80% of the total bank liquidity creation (e.g., Berger and Bouwman 2009).

I then examine how CEO inside debt holdings are related to bank liquidity creation, conditional on whether the banks are TARP recipients. Past literature finds that the injection of capital through TARP increases the risk-taking strategies of the bank (e.g., Black and Hazelwood 2012; Li 2013; Duchin and Sosyura 2014) because the interests of its shareholders and managers are aligned to take more risks in order to maximize their own wealth at the expense of the taxpayers. Although TARP recipients are meant to take less risks in order to mitigate bank risk and lower systemic risk, empirical studies find that they take more risks after the injection of capital. Thus, it is important to examine whether TARP recipients create more liquidity in the market as the inside debt holdings of their CEOs increase. This analysis has the potential to determine whether CEO inside debt holdings still inhibit bank liquidity creation, even in the case of capital injection. From this study, I find that the negative effects of debt-based compensation on bank liquidity creation are driven by TARP banks. This suggests that CEOs in TARP banks manage traditional banking activities more conservatively than CEOs in non-TARP banks because of their increased debt incentives. This increased conservatism could be due to the intensive monitoring by both shareholders and regulators after the injection of capital. Because previous studies have already shown that TARP banks take more risks after the injection of capital, the results posited here show that the implementation of TARP do not lower bank risks or encourage a depressed economy in terms of liquidity creation.

This paper contributes to the existing literature on CEO inside debt holdings. The majority of studies concerning the effects of CEO inside debt holdings on risk-taking focus on non-financial companies (e.g., Sundaram and Yermack 2007; Chava, Kumar, and Warga 2010; Cassell, Huang, Sanchez, and Stuart 2012; Anantharaman, Fang, and Gong 2014; Phan 2014). While previous studies examine the effects of inside debt holdings of bank CEOs on payout policy, default risk, bank-specific risk, and systemic risk (e.g., Srivastav, Armitage, and Hagendorff 2014; Bennett, Guntay, and Unal 2015; van Bekkum 2016), my study focuses on the effects of debt-like compensation on bank liquidity creation, a traditional banking activity. Despite van Bekkum's (2016) study, where he proves that CEO inside debt holdings decrease non-traditional banking activities, suggesting that CEO inside debt compensation increases traditional banking activities, he does not explore the effects of CEO inside debt holdings on traditional banking activities. Accordingly, my paper contributes to the existing literature on inside debt holdings of bank CEOs by exploring whether bank CEOs with high inside debt holdings create less liquidity to the market. To the best of my knowledge, there is no study that examines the effects of CEO inside debt holdings on traditional banking activities such as bank liquidity creation.

This paper also contributes to existing literature concerning the determinants of bank liquidity creation. Berger and Bouwman (2009) introduce comprehensive bank liquidity creation measures, and there are many empirical studies that examine the determinants of bank liquidity creation. Berger and Bouwman (2009) examine the relationship between equity ratio and bank liquidity creation; Diaz and Huang (2017) examine the relationship between bank governance and liquidity creation; Distinguin, Roulet, and Tarazi (2013) investigate the relation between bank regulatory capital and bank liquidity creation; Berger, Bouwman, Kick, and Schaeck (2016) examine effects of regulatory interventions and capital support on bank liquidity creation in Germany; Berger and Bouwman (2017) investigate the relation between liquidity creation, monetary policy, and financial crises; Berger, Guedhami, Kim, and Li (2018) investigate the relation between bank liquidity hoarding, which is opposite to bank liquidity creation, and economic policy uncertainty; and Jiang, Levine, and Lin (2019) as well as Choi (2019) examine the relationship between enhanced bank competition following bank deregulation and bank liquidity creation. DeYoung and Huang (2016) investigate the relationship between option-based compensation and bank liquidity creation. They find that CEO pay-performance incentives (delta) reduce both positive liquidity creation externalities and negative systemic risk externalities; they also find that pay-risk incentives increase both externalities. This paper contributes to the existing literature by investigating whether CEOs with high inside debt holdings increase bank liquidity creation.

The results presented in this study have strong implications for policies regarding executive compensation structures within the banking industry. In the banking industry, regulators take bank soundness into account when they design regulatory policies (e.g., bank capital requirement). Regulators are also interested in local economic growth. To encourage depressed local markets, they want banks to create more liquidity in the market. Based on the empirical results of my paper and of previous studies, implementing policies concerning CEO compensation structure could be a method of achieving these aims.

When regulators design policies for the banking industry, they need to consider the effects of CEO inside debt holdings on both bank risk and bank liquidity creation, as enhanced CEO inside debt holdings would result in two polar results: lower bank liquidity creation and better bank soundness for the bank itself and the financial industry as a whole. Regulators could increase bank liquidity creation by imposing lower CEO inside debt holding requirements, which would make the banks prone to some risky situations. Debt-based compensation may be a double-edged sword for the design of banking policies concerning bank liquidity creation and bank soundness. This also suggests that regulators should design bank-specific policies regarding bank governance because banks can impact local markets and market participants.

The remainder of this paper is organized as follows: Section 2 provides a literature review. Section 3 describes the data on CEO inside debt holdings, bank liquidity creation, and the data on controls. Section 4 provides the empirical results on the relationship between CEO inside debt holdings and bank liquidity creation. Section 5 concludes the paper.

4.2 Literature Review

4.2.1 Inside Debt Compensation

Shareholders have strong incentives to take on risky projects at the expense of debtholders. On the other hand, debtholders have fewer incentives to take on said projects, even though the projects are positive net present value projects; this is mainly due to the fact that debtholders have limited expectations of profit from such risk-taking.

Managers have less incentives to take risks than shareholders because their wealth portfolio may not be sufficiently diversified. To motivate the risk-taking incentives of CEOs, firms reward them with incentive compensations such as stock options, stock grants, performance-based cash bonuses, etc. In this case, CEOs are incentivized to take more risks in order to maximize their shareholders' value and their own wealth: Their interests are aligned with those of the shareholders. However, they take excessive risks at the expense of debtholders.

Jensen and Meckling (1976) suggest that inside debt holdings can resolve conflicts of agency between debtholders and agents. If a CEO's personal leverage is equal to the company's leverage, then the CEO has an incentive to invest in new projects in a more careful manner.

Consistent with the hypothesis above, past literature on CEO inside debt finds that debt-based compensation is associated with more conservative decision-making in terms of corporate policies. To be more specific, Sundaram and Yermack (2007) find that CEO inside debt holdings increase with the age of the CEO; they also find that CEO inside debt holdings increase the distance to default, suggesting that CEO debt compensation decreases the risk of default.

Using only pension compensation, Chava, Kumar, and Warga (2010) examine whether CEO debt-like compensation is associated with covenant choice. They find a reverse relationship between CEO pension compensation and the use of the major types of covenants, including investment restrictions, dividend restrictions, and subsequent financing restrictions. The results suggest that CEO pension compensation plays a disciplinary role. Using both pension and deferred compensation, Anantharaman, Fang, and Gong (2014) find that lenders care about CEO's inside debt holdings when they create loans for them. CEO inside debt holdings are negatively related to promised yields and the number of covenants.

Cassell, Huang, Sanchez, and Stuart (2012) find a negative relationship between CEO inside debt holdings and stock return volatility, research and development expenses, and financial leverage. This suggests that CEOs with high inside debt holdings manage their companies more conservatively. They also find that CEO inside debt holdings are positively associated with company diversification and asset liquidity, suggesting that CEOs manage assets more conservatively. Phan (2014) explores the role of CEO inside debt holdings in mergers and acquisitions (M&A). Consistent with theoretical expectations, this paper finds a negative relationship between CEO inside debt holdings and the propensity of M&A.

Because most studies regarding CEO compensation exclude financial companies, there are few studies examining the effects of CEO inside debt holdings within the banking industry. Bennett, Guntay, and Unal (2015) investigate whether CEO inside debt was related to bank default risk and bank performance during the recent financial crisis. They find that higher CEO inside debt holdings were associated with lower default risk and better performance during the crisis period.

Van Bekkum (2016) examines whether CEO inside debt holdings in the pre-crisis period were associated with both bank-specific risk and systemic risk. He finds results that are consistent with theoretical expectation. Specifically, van Bekkum finds a reverse relation between CEO inside debt holdings and bank-specific and systemic risk. Consistent with previous literature, this paper proves that CEOs with high inside debt holdings decrease low-quality assets, write-downs, and non-interest income.

Although van Bekkum (2016) finds a negative relationship between CEO inside debt holdings and the fraction of non-traditional banking activities, there is no further analysis provided on the effects of CEO inside debt holdings on traditional banking activities. In this paper, the topic I explore sufficiently addresses this gap in the literature.

4.2.2 Bank Liquidity Creation

Berger and Bouwman (2009) allow researchers to investigate various theoretical views on bank liquidity creation by providing four bank liquidity creation measures according to the classification of loans by category or maturity and the inclusion of off-balance sheet activities.

The most comprehensive bank liquidity creation measure is “cat fat,” which classifies loans by categories and includes off-balance sheet items in liquidity creation calculation. Its comprehensiveness is due to the fact that its category-based loan classification is economically more accurate than a maturity-based loan classification. This accuracy can be seen in the category-based approach’s consideration of business loans as illiquid, regardless of their maturity; in general, banks are not able to easily dispose of their business loans to meet their liquidity needs.

On the other hand, the category-based approach considers residential mortgages and consumer loans as semi-liquid: For banks, it is relatively easier to securitize and sell these loans to meet demands for liquid funds. This suggests that the intrinsic nature of different loans, based on their category, is more important than the maturity of the loans when bank liquidity creation is measured.

In addition to loan classification, the inclusion of off-balance sheet activities is important in constructing bank liquidity creation measures. Holmström and Tirole (1998) and Kashyap, Rajan, and Stein (2002) suggest that banks create liquidity through off-balance activities such as loan commitments, letters of credit, etc. From this, it is clear why the “cat fat” approach is the most comprehensive measure of liquidity creation.

In their study, which comprised all US commercial banks in the period 1993 to 2003, they find that the US banking industry created \$2.84 trillion in liquidity in 2003, which is equivalent to \$4.56 of liquidity creation per \$1 of bank equity capital. They find that liquidity creation has grown substantially over the sample period (1993 to 2003) by using the “cat fat” measure. They also report that liquidity creation differs considerably among banks of different size: Banks categorized as “large” banks, comprising roughly 2% of their sample, accounted for 81% of bank liquidity creation. In addition, off-balance sheet items played a significant role in generating liquidity for banks of all sizes.

Even though Berger and Bouwman (2009) provide all of the comprehensive liquidity creation measures, there are still too few empirical studies exploring the role of banks as liquidity creators. Previous literature has studied the relationship between liquidity creation and equity ratio (e.g., Berger and Bouwman 2009), corporate governance (e.g., Diaz and Huang 2017), bank deregulation (e.g., Jiang, Levine, and Lin 2019; Choi 2019), option-based compensation, option delta and option vega (e.g., DeYoung and Huang 2016), monetary policy and financial crises (e.g., Berger and Bouwman 2017), regulatory interventions and capital support (e.g, Berger, Bouwman, Kick, and Schaeck 2016), regulatory capital (e.g., Distinguin, Roulet, and Tarazi 2013), and real economic output (e.g., Berger and Sedunov 2017).

Unlike these studies, my paper investigates whether inside debt holdings of bank CEOs are associated with bank liquidity creation. I also use instrumental variables to mitigate any endogeneity concerns. The empirical evidence of this paper suggests important implications for policy-making: Regulators must consider the effects of CEO inside debt holdings on both bank risk and bank liquidity creation when they design policies for the banking industry. This is due to the fact that enhanced CEO inside debt holdings would result in two polar results: lower bank liquidity creation and better bank soundness for the bank itself and the financial industry as a whole. Debt-based compensation may be a double-edged sword for the design of liquidity creation banking policies.

4.3 Data

I compile a wide-ranging data from a variety of sources. I mainly collect CEO compensation data from Compustat Execucomp database. For bank liquidity creation data, I collect the data from Christa Bouwman's personal website.[10] In addition, I obtain balance sheet data and income statement accounting data from Standard & Poor's Compustat Fundamentals and the Bank Regulatory database, and stock prices and market capitalization data are from the Center for Research in Security Prices (CRSP). In addition, I collect board size and board independence data from Institutional Shareholder Services (formerly RiskMetrics). I obtain the list of TARP recipients among my sample banks from the U.S. Department of the Treasury.

Following Fahlenbrach and Stultz (2011), I collect all bank-year observations for

[10] Please visit a link (https://sites.google.com/a/tamu.edu/bouwman/data) if you want to download quarterly bank liquidity creation measures.

firms with Standard Industry Classification (SIC) codes between 6000 and 6300 in fiscal year 2006. Because my paper examines the relation between CEO insider debt holdings and bank liquidity creation, which is a main traditional banking activity, I exclude financial firms that do not run lending business.

To merge these data, I use PERMCO-RSSD link table that covers 1,412 banks from 1986 to 2016.[11] After merging all datasets, I have 119 bank holding companies that operate traditional banking activities during the sample period from 2006 to 2016.

4.3.1 CEO Compensation

Data on CEO compensation are collected from Compustat Execucomp database. The data is available from 1992 to 2016. However, components of my key independent variable, CEO inside debt holdings, are only available after the 2007 SEC disclosure reform, so my sample period starts after the event.

Following Chang, Fu, Low, and Zhang (2015), I remove firms with unidentified CEOs, negative CEO tenure, missing total compensation (tdc1), or zero total compensation. To identify CEOs, I firstly use both CEO indicator (ceoann) and present CEO indicator (pceo) that Compustat Execucomp provides. However, some firms still have either no CEO or multiple CEOs. To correct this issue, I use date variables that indicate when the person became the CEO (becameceo) and when the person left the CEO position (leftofc). For firms without CEOs even after performing pervious steps, I check the executive's position description variable (titleann) whether it contains words, such as "Chairman," "Chief Executive Officer," "President," etc.

[11] Federal Reserve Bank of New York shares the table that link CRSP identifier (PERMCO) with Federal Reserve identifier (RSSDID). Please visit their webpage below. (https://www.newyorkfed.org/research/banking_research/datasets.html)

I construct various CEO compensation variables. Following Cole, Daniel, and Naveen (2013), I construct pay-performance sensitivity (delta), risk-taking incentive (vega), total compensation, and the portion of cash salary variables as controls. Following Wei and Yermack (2011) and van Bekkum (2016), I construct CEO inside debt holding variable. Two main variables for inside debt compensation are total pension value (pension_value_tot) and total deferred compensation balance (defer_balnace_tot). Total pension value (pension_value_tot) is the present value of accumulated pension benefits from all the company's pension plans, and total deferred compensation balance (defer_balnace_tot) is the total aggregate balance in non-tax-qualified deferred compensation plans at the end of fiscal year. Total inside debt is the sum of pensions and deferred compensations. The CEO's debt incentive is the sum of the pension compensation and the deferred compensation, and the CEO's equity incentive is the sum of the delta of the CEO's shares of stock and the delta of CEO option holdings. The CEO personal leverage is equal to the ratio of the debt incentives to the equity incentives. The firm's debt-equity incentive ratio is the ratio of total long-term debt, including current debt, to equity market value.

4.3.2 Bank Liquidity Creation

Berger and Bouwman (2009) use a three-step procedure to construct liquidity creation measures. In Step 1, all balance sheet and off-balance sheet activities are classified as liquid, semi-liquid, or illiquid. The classification is based on the ease, cost, and time for customers to obtain liquid funds from the bank, and the ease, cost, and time for banks to dispose of their obligations in order to meet these liquidity demands. The balance sheet items are classified by product, category, and maturity. In Step 2, weights are assigned to the items classified in Step 1. In Step 3, liquidity creation is measured by combining the classified items of Step 1 and the weighted items of Step 2. According to Berger and Bouwman (2009), the ability to securitize loans is more relevant for the product category concept than the time-until-self-liquidation concept. This means that category-based loan classification is a more efficient way of measuring bank liquidity creation.

According to Berger and Bouwman (2009), the ability to securitize loans is more relevant for the product category concept than the time-until-self-liquidation concept. This means that category-based loan classification is a more efficient way of measuring bank liquidity creation.

In addition, previous studies suggest that banks create liquidity through off-balance sheet activities, such as loan commitments, letters of credit, etc. Consistent with previous studies, Berger and Bouwman (2009) find that a significant portion of bank liquidity is created from off-balance sheet activities. In my data, I also find that roughly 33% of liquidity is created from off-balance sheet activities, suggesting that off-balance sheet activities are negligible when I measure bank liquidity creation. Thus, I use the "cat fat" bank liquidity creation measure.

4.3.3 Control Variables

I follow prior studies to control for several bank characteristics and CEO characteristics that could affect bank liquidity creation.

I include a group of bank-level variables in my model. I include bank size, which is natural log of gross total assets (GTA), and equity capital ratio, which is the ratio of equity to GTA. I also control for Z-Score, which is the distance to default. Z-score is equal to the sum of the bank's return on assets and the equity ratio, divided by the standard deviation of the return on assets. I also control for ROA and Tobin's q is the sum of the bank's market value of equity and the book value of liabilities, divided by the book value of assets. Furthermore, I control for market leverage, which is total assets minus equity book value, divided by total assets plus equity market value minus equity book value, and market-to-book ratio.

CEO characteristic control variables include natural log of total compensation, the portion of cash salary, pay-performance sensitivity (delta), and risk-taking incentives (vega). I also control for board independence and board size.

4.3.4 Summary Statistics

Summary statistics are presented in Table 1. Panel A of Table 1 shows the bank fiscal-year summary statistics for CEO compensation, bank liquidity creation, and bank-specific control variables. For CEO compensation structure, the banks in my sample have an average CEO personal leverage of roughly 0.262 and an average total annual compensation of roughly $2.6 million. Bank liquidity creation is roughly 50% of the gross total assets, on average. In terms of the characteristics of the banks in my sample, they have an average equity ratio of 11%, a Tobin's q ratio of 1.039, a return on assets (ROA) of 2.1%, and a market-to-book ratio of 28.9%. The banks in my sample have approximately thirteen directors in the boardroom, and 78.9% of the directors are independent directors. Among the sample banks, about two-thirds of the sample banks are TARP recipients.

Panel B of Table 1 reports summary statistics conditional on bank size and differences in variables between large banks and small and medium-sized banks. I classify a bank as a "large" bank if the bank is larger than the median bank size. In terms of CEO compensation, large banks have a larger total compensation than small and medium-sized banks. Large banks also have larger debt and equity incentives than small and medium-sized banks. However, large banks have significantly lower fractions of cash salary. These characteristics suggest that CEOs in large banks are more incentivized by equity- and debt-based compensations. From the perspective of bank liquidity creation, Panel B of Table 1 shows that large banks have a higher ratio of bank liquidity creation to total gross assets than smaller banks. Panel B also shows that liquidity creation of large banks is driven by off-balance sheet activities. Consistent with past literature concerning boards of directors and TARP, I find that large banks have larger boards, higher board independence, and are more likely to receive TARP funds.

Panel C of Table 1 reports summary statistics, depending on whether a bank receives TARP funds, and compares the variables between TARP banks and non-TARP banks. Relative to non-TARP banks, and consistent with Bayazitova and Shivdasani's (2011) study, TARP banks tend to be larger, be higher liquidity creators, have higher debt incentives, have higher risk-taking incentives, have larger total compensation packages, and have less fraction of cash salary. In terms of the board characteristics of TARP banks, they exhibit a higher fraction of independent directors and a larger number of directors than non-TARP banks. Both Panels B and C of Table 1 suggest that large banks (TARP banks) are different from small and medium-sized banks (non-TARP banks) in terms of CEO compensation structure, bank liquidity creation behavior, and bank-specific characteristics.

Table 4.1 Summary Statistics

This table presents the summary statistics about CEO compensation, bank characteristics, and bank liquidity creation variables. The sample consists of 119 banks from 2006 to 2016. Panel A presents fiscal year-level summary statistics, Panel B presents fiscal year-level summary statistics by bank size, Panel C presents fiscal year-level summary statistics by TARP recipients. Detailed information about variables are available in Appendix.

Panel A. Summary Statistics

Compensation Variables	N	Mean	SD	P25	P50	P75	Source
Inside_Debt	819	0.262	0.249	0.035	0.191	0.445	Compustat Execucomp
ln_delta	802	4.911	1.506	3.880	4.783	5.956	Compustat Execucomp
ln_vega	802	3.029	2.021	1.395	3.234	4.390	Compustat Execucomp
Delta	802	440.30	1021.00	47.44	118.50	385.00	Compustat Execucomp
Vega	802	111.30	239.20	3.03	24.38	79.61	Compustat Execucomp
LN(TDC1)	822	7.871	1.032	7.146	7.789	8.517	Compustat Execucomp
Cash_TDC1	822	0.409	0.240	0.222	0.357	0.576	Compustat Execucomp
Bank Liquidity Creation	**N**	**Mean**	**SD**	**P25**	**P50**	**P75**	**Source**
LC	822	52,080,000	152,900,000	2,872,000	6,406,000	16,640,000	Call Report
LC_A	822	-3,471,000	42,110,000	219,968	1,314,000	3,588,000	Call Report
LC_L	822	23,390,000	73,600,000	1,530,000	3,172,000	9,724,000	Call Report
LC_OBS	822	32,160,000	113,800,000	587,475	1,546,000	6,374,000	Call Report
LC_GTA	822	0.502	0.315	0.379	0.488	0.583	Call Report
LC_A_GTA	822	0.111	0.146	0.038	0.129	0.211	Call Report
LC_L_GTA	822	0.224	0.090	0.172	0.234	0.282	Call Report
LC_OBS_GTA	822	0.168	0.309	0.071	0.111	0.159	Call Report
Firm-Characteristics	**N**	**Mean**	**SD**	**P25**	**P50**	**P75**	**Source**
Bank Size	822	16.87	1.57	15.77	16.46	17.63	Call Report
EQRAT	822	0.110	0.027	0.095	0.108	0.122	Call Report
Z-Score	814	35.74	141.40	13.69	22.47	33.77	Compustat
MTB	817	0.289	0.105	0.220	0.266	0.336	Compustat, CRSP
Q	716	1.039	0.053	1.005	1.031	1.064	Compustat, CRSP
ROA	822	0.021	0.011	0.018	0.022	0.026	Compustat
Board Size	822	2.553	0.208	2.398	2.565	2.708	ISS
Board Indep	822	0.789	0.113	0.722	0.800	0.889	ISS
TARP	822	0.605	0.489	0	1	1	The U.S. Treasury

(Continued from the previous page)

Panel B. Summary Statistics: Large vs. Small Banks

This Panel presents the summary statistics by bank size. The sample consists of 119 banks from 2006 to 2016. The last two column in this Panel presents the mean difference between large banks and medium/small banks and whether they are significantly different, based on the unpaired t-statistics, computed for unequal variance and unequal observations. The null hypothesis for this t-test is that the mean difference is zero. Detailed information about variables are available in Appendix.

	Large Banks				Small/Medium Banks				
Compensation Variables	N	Mean	SD	P50	N	Mean	SD	P50	Diff.
Inside_Debt	410	0.281	0.248	0.228	409	0.243	0.248	0.153	**0.038**
ln_delta	405	5.532	1.451	5.542	397	4.277	1.281	4.16	**1.255**
ln_vega	405	3.869	2.016	4.1	397	2.172	1.631	2.457	**1.697**
Delta	405	716.6	1,361	254.1	397	158.5	252.2	63.07	**558.100**
Vega	405	194	311.4	59.35	397	26.99	51.38	10.67	**167.010**
LN(TDC1)	411	8.501	0.936	8.454	411	7.241	0.678	7.25	**1.260**
Cash_TDC1	411	0.296	0.201	0.241	411	0.523	0.223	0.478	**-0.227**
Bank Liquidity Creation	N	Mean	SD	P50	N	Mean	SD	P50	
LC	411	100,800,000	205,100,000	16,640,000	411	3,407,000	1,901,000	3,033,000	**97,393,000**
LC_A	411	-7,931,000	59,240,000	3,481,000	411	990,123	1,129,000	881,631	**-8,921,123**
LC_L	411	45,110,000	99,500,000	9,724,000	411	1,680,000	883,636	1,574,000	**43,430,000**
LC_OBS	411	63,590,000	154,700,000	6,374,000	411	737,332	575,308	596,471	**62,852,668**
LC_GTA	411	0.549	0.415	0.519	411	0.456	0.152	0.463	**0.093**
LC_A_GTA	411	0.080	0.148	0.117	411	0.142	0.138	0.156	**-0.062**
LC_L_GTA	411	0.224	0.106	0.243	411	0.223	0.071	0.225	0.001
LC_OBS_GTA	411	0.244	0.420	0.149	411	0.092	0.054	0.085	**0.153**
Firm-Characteristics	N	Mean	SD	P50	N	Mean	SD	P50	
Bank Size	411	18.02	1.40	17.63	411	15.71	0.53	15.77	**2.310**
EQRAT	411	0.106	0.021	0.105	411	0.113	0.031	0.111	**-0.007**
Z-Score	407	40.34	198.30	21.54	407	31.14	25.58	23.57	9.200
MTB	406	0.287	0.110	0.264	411	0.292	0.101	0.272	-0.005
Q	369	1.027	0.045	1.022	347	1.053	0.058	1.040	**-0.026**
ROA	411	0.021	0.010	0.022	411	0.021	0.013	0.023	0.000
Board Size	411	2.608	0.172	2.639	411	2.498	0.226	2.485	**0.110**
Board Indep	411	0.808	0.105	0.833	411	0.771	0.118	0.786	**0.037**
TARP	411	0.749	0.434	1	411	0.460	0.499	0	**0.289**

(Continued from the previous page)

Panel C. Summary Statistics: TARP Recipients vs. Non-TARP Recipients

This Panel presents the summary statistics by bank size. The sample consists of 119 banks from 2006 to 2016. The last two column in this Panel presents the mean difference between TARP recipients and non-TARP recipients and whether they are significantly different, based on the unpaired t-statistics, computed for unequal variance and unequal observations. The null hypothesis for this t-test is that the mean difference is zero. Detailed information about variables are available in Appendix.

	TARP				Non-TARP				
Compensation Variables	N	Mean	SD	P50	N	Mean	SD	P50	Diff.
Inside_Debt	495	0.293	0.260	0.248	324	0.215	0.222	0.153	**0.078**
ln_delta	486	4.932	1.511	4.706	316	4.878	1.499	4.875	0.054
ln_vega	486	3.098	2.082	3.219	316	2.923	1.923	3.241	0.175
Delta	486	497.80	1217.00	109.60	316	351.90	598.20	130.00	**145.900**
Vega	486	126.20	257.20	24.01	316	88.37	206.70	24.56	**37.830**
LN(TDC1)	497	8.051	1.062	8.050	325	7.596	0.919	7.548	**0.455**
Cash_TDC1	497	0.385	0.236	0.331	325	0.447	0.243	0.401	**-0.062**
Bank Liquidity Creation	N	Mean	SD	P50	N	Mean	SD	P50	
LC	822	73,830,000	180,700,000	9,730,000	325	18,830,000	86,050,000	3,430,000	**55,000,000**
LC_A	822	-6,635,000	52,680,000	2,060,000	325	1,369,000	14,350,000	744,072	**-8,004,000**
LC_L	822	34,630,000	91,180,000	4,993,000	325	6,213,000	22,510,000	1,774,000	**28,417,000**
LC_OBS	822	45,840,000	132,200,000	2,373,000	325	11,250,000	72,840,000	858,067	**34,590,000**
LC_GTA	822	0.519	0.293	0.508	325	0.477	0.346	0.463	**0.042**
LC_A_GTA	822	0.111	0.141	0.130	325	0.111	0.154	0.128	0.000
LC_L_GTA	822	0.223	0.094	0.241	325	0.224	0.084	0.222	-0.001
LC_OBS_GTA	822	0.185	0.295	0.119	325	0.141	0.328	0.097	**0.044**
Firm-Characteristics	N	Mean	SD	P50	N	Mean	SD	P50	
Bank Size	497	17.32	1.63	16.83	325	16.17	1.16	15.97	**1.150**
EQRAT	497	0.110	0.019	0.109	325	0.109	0.036	0.105	0.001
Z-Score	497	36.85	179.80	20.09	317	34.00	26.67	25.79	2.850
MTB	496	0.272	0.101	0.253	321	0.316	0.106	0.304	**-0.044**
Q	440	1.026	0.046	1.020	276	1.061	0.057	1.054	**-0.035**
ROA	497	0.019	0.011	0.021	325	0.023	0.012	0.024	**-0.004**
Board Size	497	2.567	0.181	2.565	325	2.533	0.242	2.565	**0.034**
Board Indep	497	0.809	0.107	0.833	325	0.760	0.116	0.778	**0.049**
Large Bank	497	0.620	0.486	1	325	0.317	0.466	0	**0.303**

4.4 Empirical Results

4.4.1 Does CEO Inside Debt Decrease Bank Liquidity Creation?

In this section, I report on my empirical analysis concerning the relationship between inside debt holdings of bank CEOs and bank liquidity creation. I focus on whether inside debt holdings of bank CEOs are associated with bank liquidity creation at bank level. I estimate the following ordinary least squares model:

$$LC_{it} = \beta_0 + \beta_1 Inside\ Debt_{it} + \beta_k X_{it} + \mu_i + v_t + \varepsilon_{it} \qquad (1)$$

The key dependent variable for the OLS model is bank liquidity creation measures (LC). Following Berger and Bouwman (2009), I mainly use a comprehensive bank liquidity creation measure, "cat fat," but I also use the other liquidity creation measures for robustness checks. The key independent variable is CEO inside debt holdings (Inside Debt). In the model, μ_i means bank fixed effects and v_t means year fixed effects. X_{it} is a set of control variables, including firm characteristics and CEO characteristics. ε_{it} is an error term. Standard errors are adjusted to control for clustering at the bank level.

In Table 2, I regress bank liquidity creation on CEO inside debt compensation and various control variables. In addition to CEO compensation variables, including pay-performance sensitivity, risk-taking incentives, the fraction of cash salary, and total compensation, I control for bank characteristics that are related to bank liquidity creation, including bank size, leverage, market-to-book ratio, ROA, Tobin's q, z-score, and equity ratio. I also include two governance variables: Board size and board independence.

I hypothesize that CEOs with high debt incentives would create less liquidity in the market. Even though CEOs do not create more loans, it is possible to take more risk by changing their liquidity creation strategies because they can choose to issue either illiquid loans or liquid loans to the market. They also can choose whether they use liquid liabilities or illiquid liabilities when they create loans. These decisions are related to bank liquidity creation. That is why it is not necessarily true that CEOs having higher inside debt create more liquidity in the market although van Bekkum (2016) finds that banks with these CEOs reduce non-traditional banking activities. CEOs would have more incentives to take safer projects as their debt incentives increase. Thus, I expect that CEO debt incentives are negatively related to bank liquidity creation.

Coefficient estimates in Table 2 are negative and statistically significant in Column 1. The results are consistent with the prediction above and show that a unit increase in personal leverage implies an increase in bank liquidity creation, close to 0.147 standard deviations. The results suggest that CEOs adopt conservative bank liquidity creation strategies as their inside debt increases. This result is consistent with the incentives of CEOs with higher debt-based compensation who would not take on risky investments at the expense of debtholders.

In Columns 2 to 4, I find that the negative relationship between CEO inside debt and bank liquidity creation is driven by off-balance sheet activities. Because Berger and Bouwman (2009) show that large banks create much higher fractions of liquidity through off-balance sheet activities than small and medium-sized banks, the result indicates that bank size is an important factor in the relationship between inside debt holdings and bank liquidity creation. Thus, I examine whether there are heterogenous relations between CEO inside debt and bank liquidity creation, conditional on bank size.

Table 3 reports the results, examining the relationship between CEO inside debt and bank liquidity creation, depending on bank size. Consistent with the prediction mentioned above, I find that the results are driven by large banks. The results imply that regulators should motivate CEOs in large banks if they want to encourage bank liquidity creation, as large banks occupy roughly 80% of total bank liquidity creation.

Table 4.2 Relation between CEO Inside Debt and Bank Liquidity Creation

Table 2 shows results of OLS regressions of bank liquidity creation on CEO inside debt holdings and control variables. Key dependent variable is bank liquidity creation measure, normalized by bank's gross total assets. In Column 1, I use "cat fat," which is the most comprehensive liquidity creation measure. In Columns 2-4, I decompose the "cat fat" measure into asset-side, liability-side, and off-balance sheet side liquidity creation measures. Key independent variable is CEO inside debt holdings. Inside Debt is CEO's personal leverage, which is the ratio of debt-based compensation, including pension and deferred compensation, to equity incentives, which are the sum of equity-based compensation. LN(Delta) is natural logarithm of delta, which is a pay-performance sensitivity. LN(Vega) is natural logarithm of vega, which is a risk-taking incentive. Control variables include equity ratio (EQRAT), board independence, board size, Market-to-Book ratio (MTB), ROA, Q, Size, ZSCORE, natural logarithm of total annual compensation, and the portion of cash salary. In the model, μ_i means each bank's time-invariant specific effect, and ν_t means that year specific effect. X_{it} is a set of explanatory variables, and ε_{it} is an error term, which assumes that E(ε_{it})=0 and Var(ε_{it})=σ^2. All models include year and bank fixed effects and cluster standard errors by firm. Brackets contain robust standard errors and superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	(1) Cat Fat	(2) Asset-side	(3) Liability-side	(4) Off-balance sheet
Inside Debt	-0.162**	-0.013	-0.018	-0.130**
	(0.06)	(0.02)	(0.01)	(0.05)
LN(Delta)	-0.034	-0.008	-0.010*	-0.017
	(0.02)	(0.01)	(0.01)	(0.02)
LN(Vega)	0.004	0.003	-0.001	0.001
	(0.01)	(0.00)	(0.00)	(0.01)
EQRAT	-1.025	-0.239	-0.391**	-0.395
	(1.04)	(0.28)	(0.19)	(1.00)
Board Independence	-0.226	-0.022	-0.032	-0.172
	(0.25)	(0.04)	(0.03)	(0.24)
LN(Board Size)	0.048	-0.005	0.014	0.039
	(0.06)	(0.02)	(0.02)	(0.04)
MTB	0.000	-0.050	-0.096	0.146
	(0.33)	(0.09)	(0.08)	(0.29)
ROA	3.253	1.263**	1.100**	0.890
	(2.06)	(0.56)	(0.48)	(2.04)
Q	0.112	-0.063	0.291**	-0.116
	(0.38)	(0.19)	(0.12)	(0.31)
Size	0.044	0.029	-0.014	0.029
	(0.03)	(0.02)	(0.01)	(0.03)
ZSCORE	0.004	0.001	0.001	0.002
	(0.00)	(0.00)	(0.00)	(0.00)
LN(Total Compensation)	-0.016	-0.003	0.005	-0.018
	(0.02)	(0.00)	(0.00)	(0.01)
Cash/TDC1	0.096	0.005	0.022*	0.068
	(0.09)	(0.02)	(0.01)	(0.09)
Constant	-0.015	-0.207	0.116	0.076
	(0.79)	(0.41)	(0.22)	(0.69)
Observations	594	594	594	594
Adjusted R-squared	0.053	0.158	0.499	0.020
Fixed Effects	Bank, Year	Bank, Year	Bank, Year	Bank, Year

Table 4.3 Relation between CEO Inside Debt and Bank Liquidity Creation by Size

Table 3 shows results of OLS regressions of bank liquidity creation on CEO inside debt holdings and control variables by bank size. Large bank is classified based on median value of bank size. Key dependent variable is bank liquidity creation measure, normalized by bank's gross total assets. In Column 1, I use "cat fat," which is the most comprehensive liquidity creation measure. In Columns 2-4, I decompose the "cat fat" measure into asset-side, liability-side, and off-balance sheet side liquidity creation measures. Key independent variable is CEO inside debt holdings. Inside Debt is CEO's personal leverage, which is the ratio of debt-based compensation, including pension and deferred compensation, to equity incentives, which are the sum of equity-based compensation. LN(Delta) is natural logarithm of delta, which is a pay-performance sensitivity. LN(Vega) is natural logarithm of vega, which is a risk-taking incentive. Control variables include equity ratio (EQRAT), board independence, board size, Market-to-Book ratio (MTB), ROA, Q, Size, ZSCORE, natural logarithm of total annual compensation, and the portion of cash salary. In the model, μ_i means each bank's time-invariant specific effect, and ν_t means that year specific effect. X_{it} is a set of explanatory variables, and ε_{it} is an error term, which assumes that $E(\varepsilon_{it})=0$ and $Var(\varepsilon_{it})=\sigma^2$. All models include year and bank fixed effects and cluster standard errors by firm. Brackets contain robust standard errors and superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

(Continued from the previous page)

VARIABLES	(1) Cat Fat Large	(2) Asset-side Large	(3) Liability-side Large	(4) Off-balance sheet Large	(5) Cat Fat Small	(6) Asset-side Small	(7) Liability-side Small	(8) Off-balance sheet Small
Inside Debt	-0.320***	-0.033	-0.042**	-0.244**	-0.034	-0.009	-0.012	-0.013
	(0.09)	(0.03)	(0.02)	(0.09)	(0.04)	(0.03)	(0.02)	(0.01)
LN(Delta)	-0.096**	-0.005	-0.025***	-0.066	-0.017	-0.017	0.004	-0.004
	(0.04)	(0.01)	(0.01)	(0.04)	(0.02)	(0.01)	(0.01)	(0.00)
LN(Vega)	0.022	0.001	0.004	0.018	0.011*	0.012**	0.000	-0.001
	(0.02)	(0.00)	(0.00)	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)
EQRAT	-2.063	-0.464	-0.039	-1.560	-0.422	-0.202	-0.283	0.064
	(1.87)	(0.48)	(0.33)	(1.80)	(0.49)	(0.44)	(0.20)	(0.17)
Board Independence	-0.283	0.008	-0.056	-0.235	-0.131**	-0.088*	-0.014	-0.029
	(0.38)	(0.05)	(0.04)	(0.37)	(0.05)	(0.05)	(0.04)	(0.02)
LN(Board Size)	0.007	-0.012	0.004	0.015	-0.024	-0.009	-0.003	-0.012
	(0.13)	(0.04)	(0.03)	(0.11)	(0.05)	(0.04)	(0.01)	(0.01)
MTB	-0.105	-0.136	-0.113	0.144	-0.027	0.063	-0.133*	0.044
	(0.53)	(0.14)	(0.14)	(0.46)	(0.14)	(0.13)	(0.08)	(0.05)
ROA	4.972	1.633	2.045**	1.294	1.494**	0.855	0.370	0.269
	(3.95)	(1.08)	(0.97)	(4.06)	(0.61)	(0.58)	(0.28)	(0.22)
Q	0.465	-0.175	0.524**	0.116	0.185	-0.148	0.255*	0.078
	(0.88)	(0.27)	(0.21)	(0.75)	(0.21)	(0.24)	(0.15)	(0.06)
Size	-0.001	-0.008	-0.013	0.019	0.018	0.025	-0.026**	0.018**
	(0.12)	(0.03)	(0.02)	(0.13)	(0.03)	(0.02)	(0.01)	(0.01)
ZSCORE	0.007	0.002	0.001	0.004	-0.001	0.000	-0.000	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LN(Total Compensation)	-0.011	-0.006*	0.004	-0.009	0.022	0.031*	0.005	-0.013
	(0.02)	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Cash/TDC1	0.270	0.011	-0.004	0.262	0.045	0.037	0.049***	-0.042
	(0.18)	(0.03)	(0.02)	(0.18)	(0.06)	(0.03)	(0.02)	(0.03)
Constant	0.921	0.548	-0.060	0.434	0.044	-0.177	0.316	-0.094
	(2.73)	(0.65)	(0.39)	(2.79)	(0.58)	(0.52)	(0.22)	(0.18)
Observations	315	315	315	315	279	279	279	279
Adjusted R-squared	0.065	0.150	0.443	0.043	0.298	0.185	0.661	0.150
Fixed Effects	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year

4.4.2 Does CEO Inside Debt Play a Different Role in TARP Banks?

In this section, I investigate how CEO debt incentives are related to bank liquidity creation, conditional on whether the banks receive TARP funds. The objectives of TARP's injection of capital are to support systemically important financial institutions and stabilize financial markets. However, previous studies show that TARP capital injection could lead to unintended consequences. Specifically, TARP banks take more risks after the injection of capital because they can take on risky projects at the expense of taxpayers, suggesting that both bank soundness and the economic outputs could be adversely affected by the TARP capital injection (e.g., Black and Hazelwood 2012; Li 2013; Duchin and Sosyura 2014).

In addition, previous studies suggest that capital support by the government is endogenous (e.g., Duchin and Sosyura 2012; Berger, Bouwman, Kick, and Schaeck 2016). To be specific, Duchin and Sosyura (2012) document that politically connected banks are more likely to be funded through the TARP, suggesting that the selection of TARP recipients is endogenous. In my paper, I do not claim any casual relation by exploiting TARP. Instead, I focus on stricter monitoring of TARP recipients than non-TARP recipients. For TARP recipients, there are restrictions in terms of CEO compensation structures, so the US government and shareholders should monitor the CEO compensation of TARP banks more strictly than non-TARP banks. Panel B of Table 1 shows that CEOs of TARP banks have higher debt incentives and receive higher total compensation. This is consistent with the objective of TARP and the compensation restrictions: Higher total compensation is correlated with the size of the bank, and higher debt incentives are related to the restrictions on CEO compensation.

Because previous studies find that TARP banks take on riskier projects, it is important to explore whether inside debt holdings decrease bank liquidity creation in the case of TARP banks. Creating more liquidity in the market is risky for banks, but it is beneficial for market participants in terms of social welfare. From the perspective of regulators, TARP banks taking on riskier projects and creating more market liquidity would be an unwanted result, because they want to improve bank soundness.

In Table 4, I find that the negative effects of debt-based compensation on bank liquidity creation are driven by TARP banks. Non-TARP banks create more liquidity as CEO debt incentives increase, but the liquidity is statistically insignificant and economic magnitude is small. The results indicate that CEOs of TARP banks manage traditional banking activities more conservatively than CEOs in non-TARP banks because they have more debt incentives. This could be due to the intensive monitoring by both shareholders and regulators after the injection of capital. Because previous studies have already found that TARP banks take more risks after the injection of capital, my results suggest that the implementation of TARP leads to neither lowering bank risks efficiently nor encouraging depressed economies in terms of liquidity creation.

Table 4.4 Relation between CEO Inside Debt and Bank Liquidity Creation – TARP Recipients

Table 4 shows results of OLS regressions of bank liquidity creation on CEO inside debt holdings, an interaction term between CEO inside debt and TARP banks indicator, and control variables. Key independent variable is the interaction term between CEO inside debt holdings and TARP dummy, which is equal to 1 if the bank receives TARP funds. Key dependent variable is bank liquidity creation measure, normalized by bank's gross total assets. In Column 1, I use "cat fat," which is the most comprehensive liquidity creation measure. In Columns 2-4, I decompose the "cat fat" measure into asset-side, liability-side, and off-balance sheet side liquidity creation measures. Inside Debt is CEO's personal leverage, which is the ratio of debt-based compensation, including pension and deferred compensation, to equity incentives, which are the sum of equity-based compensation. LN(Delta) is natural logarithm of delta, which is a pay-performance sensitivity. LN(Vega) is natural logarithm of vega, which is a risk-taking incentive. Control variables include equity ratio (EQRAT), board independence, board size, Market-to-Book ratio (MTB), ROA, Q, Size, ZSCORE, natural logarithm of total annual compensation, and the portion of cash salary. In the model, μ_i means each bank's time-invariant specific effect, and v_t means that year specific effect. X_{it} is a set of explanatory variables, and ε_{it} is an error term, which assumes that E(ε_{it})=0 and Var(ε_{it})=σ^2. All models include year and bank fixed effects and cluster standard errors by firm. Brackets contain robust standard errors and superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	(1) Cat Fat	(2) Asset-side	(3) Liability-side	(4) Off-balance sheet
Inside Debt	0.022	-0.012	0.007	0.026
	(0.08)	(0.04)	(0.02)	(0.06)
TARP	-0.050	0.001	0.003	-0.055
	(0.07)	(0.03)	(0.02)	(0.06)
Inside Debt X TARP	-0.221**	-0.002	-0.032	-0.187**
	(0.09)	(0.04)	(0.03)	(0.08)
LN(Delta)	-0.040	-0.008	-0.010*	-0.022
	(0.03)	(0.01)	(0.01)	(0.02)
LN(Vega)	0.004	0.003	-0.001	0.002
	(0.01)	(0.00)	(0.00)	(0.01)
EQRAT	-1.126	-0.241	-0.410**	-0.475
	(1.05)	(0.29)	(0.20)	(1.00)
Board Independence	-0.213	-0.022	-0.031	-0.160
	(0.24)	(0.04)	(0.03)	(0.23)
LN(Board Size)	0.048	-0.005	0.015	0.038
	(0.06)	(0.02)	(0.02)	(0.05)
MTB	-0.022	-0.050	-0.096	0.123
	(0.32)	(0.09)	(0.08)	(0.29)
ROA	3.320	1.261**	1.095**	0.963
	(2.07)	(0.55)	(0.49)	(2.05)
Q	0.205	-0.063	0.297**	-0.030
	(0.37)	(0.19)	(0.11)	(0.30)
Size	0.040	0.029	-0.015	0.027
	(0.03)	(0.02)	(0.01)	(0.02)
ZSCORE	0.004	0.001	0.001	0.002
	(0.00)	(0.00)	(0.00)	(0.00)
LN(Total Compensation)	-0.018	-0.003	0.005	-0.020
	(0.01)	(0.00)	(0.00)	(0.01)
Cash/TDC1	0.095	0.005	0.022*	0.068
	(0.09)	(0.02)	(0.01)	(0.09)
Constant	-0.055	-0.206	0.120	0.031
	(0.77)	(0.41)	(0.22)	(0.66)
Observations	594	594	594	594
Adjusted R-squared	0.058	0.155	0.499	0.024
Control Variables	Yes	Yes	Yes	Yes
Fixed Effects	Bank, Year	Bank, Year	Bank, Year	Bank, Year

4.4.3 Potential Endogeneity Issues

To mitigate any endogeneity concerns, I use lagged independent variables and control for time-invariant bank characteristics, such as bank culture and time trends. However, this is insufficient in resolving the endogeneity problems. Omitted variables could drive my results because many potentially omitted variables would not be differenced out by controlling for limited control variables, including bank characteristics, CEO characteristics, and bank and year fixed effects. Unobserved omitted variables that affect both CEO inside debt compensation and bank liquidity creation could result in spurious correlations between CEO debt incentives and bank liquidity creation. One possible example is CEO's optimistic view about their banks. If CEOs expect positive future performance, then they would want to have more equity-based compensation rather than debt-like compensation. This leads to lower inside debt compensation. Also, CEO optimism on bank performance is positively correlated with bank liquidity creation (e.g., Huang, Chen, and Chen 2018). This could make estimated coefficients biased.

On the other hand, reverse causality may not be a severe concern because there is no clear economic channel to prove that lower bank liquidity creation leads to higher CEO debt compensation. To be specific, CEO's debt incentives encourage CEOs to run the businesses conservatively, suggesting that debt-based compensation is a way to discourage CEOs to take risky projects. In this sense, banks with low liquidity creation have no incentives to provide their CEOs more debt-like compensation because their CEOs already take a conservative stand on their bank liquidity creation strategies.

I mitigate such concerns by using instrumental variables. Following Cassell, Huang, Sanchez, and Stuart (2012) and van Bekkum (2016), I hypothesize that the age of CEOs could be a potentially valid instrument for CEO inside debt incentives. Table 5 reports the results.

In the first stage, I regress a potentially endogenous variable, CEO inside debt holdings, on an instrument and on all of the control variables, including bank and year fixed effects. In the second stage, I regress bank liquidity creation, normalized by total gross assets, on the predicted value for CEO inside debt holdings and on all of the control variables.

For a condition to be classified as a valid instrument, it must satisfy two conditions: Relevance condition and exclusion restriction. For the relevance condition, the instrumental variable should be correlated with CEO inside debt, but it should not directly affect bank liquidity creation. The first-stage regression shows that the instrument is valid in terms of the relevance condition. For the exclusion restriction, the instrumental variable must be uncorrelated with the error term, meaning that the instrumental variable cannot directly explain bank liquidity creation. The instrumental variable should explain the dependent variable only, through its effect on CEO inside debt. Because the exclusion condition is not testable, the underlying economic argument is important.

Previous studies use executive age as an instrumental variable for debt-based compensation, including pension value and deferred compensation (e.g., Cassell, Huang, Sanchez, and Stuart 2012; van Bekkum 2016). It is straightforward to surmise that executive age mechanically increases debt-like compensation. As Sundaram and Yermack (2007) find that CEO age is positively related to inside debt incentives, the relevance condition is satisfied. However, the instrumental variable must not be correlated with bank liquidity creation to satisfy the exclusion condition, except through the control variables in the model. It is difficult to argue that the exclusion restriction for this instrumental variable is satisfied. Simultaneously, it is also difficult to argue that the exclusion restriction is clearly violated because there are two strands of studies that support two opposite theories.

On the one hand, Yim (2013) documents the negative relation between CEO age and risk-taking in the M&A market. Consistent with this finding, Berger, Kick, and Schaeck (2014) find the negative relation between executive age and bank risk-taking. These suggest that older executives/CEOs tend to be risk-averse. On the other hand, Kovalchik, Camerer, Grether, Plott, and Allman (2005) suggest that older individuals' economic decisions are less biased than younger individuals. Also, Agarwal, Driscoll, Gabaix, and Laibson (2009) find that middle-aged individuals make fewer financial mistakes than older and younger individuals, suggesting that a degree of precision of financial decision making could be correlated with age. Based on the findings of previous studies, it is possible that older CEOs may decrease bank liquidity creation to take less risk and enjoy a "quiet life." However, it is also plausible that older CEOs may increase bank liquidity creation because they have extensive experience to have a sophisticated liquidity creation strategy based on the information they have. This decision could lead to increase in bank liquidity creation. Thus, it is difficult to exhaustively rule out one possibility over another.

Table 5 and 6 report the first-stage and second-stage results. Column 1 of Table 5 shows that CEO inside debt is positively and significantly related to CEO age. The first stage coefficients on the instrument have the expected signs and are statistically significant. Also, the Kleibergen-Paap Wald F-statistic is around 34, so it indicates that CEO age would not be a weak instrument. Using CEO age as an instrument, the second stage IV regression shows that the coefficient on predicted CEO inside debt is negative. In terms of magnitude, the coefficient is more negative than the coefficient in the base regression model.

Overall, the results of IV regressions in Tables 5 and 6 are consistent with base regressions. For the comprehensive liquidity creation measure, I find that CEO inside debt negatively affects bank liquidity creation. Same as results of OLS regressions, I also find that the negative effects of CEO inside debt on bank liquidity creation are driven by off-balance sheet liquidity creation and large banks. The analysis using instrumental variables in this section mitigates any endogeneity concerns and enhances the validity of the main results.

Table 4.5 Relation between CEO Inside Debt and Bank Liquidity Creation – IV Regression

Table 5 shows results of instrumental variable (IV) regressions of bank liquidity creation on CEO inside debt holdings and control variables. Key dependent variable is bank liquidity creation measure, normalized by bank's gross total assets. Column 1 reports the first stage of an instrumental variables (IV) regression with CEO age as an instrument for CEO inside debt. In Column 2, I use "cat fat," which is the most comprehensive liquidity creation measure. In Columns 3-5, I decompose the "cat fat" measure into asset-side, liability-side, and off-balance sheet side liquidity creation measures. Key independent variable is CEO inside debt holdings. Inside Debt is CEO's personal leverage, which is the ratio of debt-based compensation, including pension and deferred compensation, to equity incentives, which are the sum of equity-based compensation. LN(Delta) is natural logarithm of delta, which is a pay-performance sensitivity. LN(Vega) is natural logarithm of vega, which is a risk-taking incentive. Control variables include equity ratio (EQRAT), board independence, board size, Market-to-Book ratio (MTB), ROA, Q, Size, ZSCORE, natural logarithm of total annual compensation, and the portion of cash salary. In the model, μ_i means each bank's time-invariant specific effect, and v_t means that year specific effect. X_{it} is a set of explanatory variables, and ε_{it} is an error term, which assumes that $E(\varepsilon_{it})=0$ and $Var(\varepsilon_{it})=\sigma^2$. All models include year and bank fixed effects and cluster standard errors by firm. Brackets contain robust standard errors and superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

(Continued from the previous page)

	(1) Cat Fat	(2) Cat Fat	(3) Asset-side	(4) Liability-side	(5) Off-balance sheet
Inside Debt		-0.219**	-0.027	-0.025	-0.167*
		(0.10)	(0.04)	(0.03)	(0.09)
LN(Delta)	-0.145***	-0.041*	-0.010	-0.010	-0.021
	(0.03)	(0.02)	(0.01)	(0.01)	(0.02)
LN(Vega)	0.038***	0.005	0.004	-0.001	0.002
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
EQRAT	1.557**	-0.916	-0.213	-0.378*	-0.325
	(0.78)	(1.07)	(0.29)	(0.19)	(1.02)
Board Independence	0.075	-0.215	-0.019	-0.030	-0.165
	(0.11)	(0.24)	(0.04)	(0.03)	(0.23)
LN(Board Size)	-0.042	0.050	-0.005	0.014	0.040
	(0.08)	(0.05)	(0.02)	(0.02)	(0.04)
MTB	0.181	0.012	-0.047	-0.095	0.154
	(0.29)	(0.32)	(0.08)	(0.08)	(0.29)
ROA	-1.083	3.131	1.234**	1.085**	0.812
	(1.22)	(2.06)	(0.55)	(0.45)	(2.05)
Q	-0.405	0.085	-0.069	0.288**	-0.133
	(0.47)	(0.37)	(0.18)	(0.11)	(0.31)
Size	0.063	0.050*	0.031*	-0.014	0.033
	(0.04)	(0.03)	(0.02)	(0.01)	(0.03)
ZSCORE	0.001	0.004	0.001	0.001	0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LN(Total Compensation)	0.020*	-0.015	-0.003	0.005	-0.017
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
Cash/TDC1	0.011	0.099	0.006	0.023*	0.070
	(0.05)	(0.08)	(0.02)	(0.01)	(0.09)
Instrument:					
LN(CEO Age)	1.358***				
	(0.23)				
Kleibergen-Paap rk Wald F statistic	34.44				
Regression	First Stage	IV	IV	IV	IV
Observations	588	588	588	588	588
Fixed Effects	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year

Table 4.6 Relation between CEO Inside Debt and Bank Liquidity Creation – IV Regression (Size)

Table 6 shows results of instrumental variable (IV) regressions of bank liquidity creation on CEO inside debt holdings and control variables. Key dependent variable is bank liquidity creation measure, normalized by bank's gross total assets. Column 1 reports the first stage of an instrumental variables (IV) regression with CEO age as an instrument for CEO inside debt. In Column 2, I use "cat fat," which is the most comprehensive liquidity creation measure. In Columns 3-5, I decompose the "cat fat" measure into asset-side, liability-side, and off-balance sheet side liquidity creation measures. Key independent variable is CEO inside debt holdings. Inside Debt is CEO's personal leverage, which is the ratio of debt-based compensation, including pension and deferred compensation, to equity incentives, which are the sum of equity-based compensation. LN(Delta) is natural logarithm of delta, which is a pay-performance sensitivity. LN(Vega) is natural logarithm of vega, which is a risk-taking incentive. Control variables include equity ratio (EQRAT), board independence, board size, Market-to-Book ratio (MTB), ROA, Q, Size, ZSCORE, natural logarithm of total annual compensation, and the portion of cash salary. In the model, μ_i means each bank's time-invariant specific effect, and ν_t means that year specific effect. X_{it} is a set of explanatory variables, and ε_{it} is an error term, which assumes that $E(\varepsilon_{it})=0$ and $Var(\varepsilon_{it})=\sigma^2$. All models include year and bank fixed effects and cluster standard errors by firm. Brackets contain robust standard errors and superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

(Continued from the previous page)

VARIABLES	(1) Large	(2) Cat Fat Large	(3) Asset-side Large	(4) Liability-side Large	(5) Off-balance sheet Large	(6) Small	(7) Cat Fat Small	(8) Asset-side Small	(9) Liability-side Small	(10) Off-balance sheet Small
Inside Debt		-0.389*	-0.062	-0.013	-0.314*		-0.089	-0.021	-0.043	-0.024
		(0.21)	(0.05)	(0.04)	(0.19)		(0.07)	(0.07)	(0.03)	(0.02)
LN(Delta)	-0.175***	-0.105***	-0.009	-0.021**	-0.075**	-0.116***	-0.023	-0.018	0.000	-0.006
	(0.03)	(0.04)	(0.01)	(0.01)	(0.04)	(0.04)	(0.02)	(0.02)	(0.01)	(0.00)
LN(Vega)	0.052***	0.025	0.002	0.002	0.021	0.024**	0.013**	0.012**	0.001	-0.000
	(0.01)	(0.02)	(0.00)	(0.00)	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
EQRAT	0.706	-1.981	-0.430	-0.074	-1.477	1.266	-0.354	-0.188	-0.244	0.078
	(1.29)	(1.86)	(0.49)	(0.34)	(1.79)	(0.83)	(0.47)	(0.42)	(0.19)	(0.16)
Board Independence	0.112	-0.276	0.011	-0.059*	-0.228	-0.015	-0.119**	-0.086	-0.006	-0.027
	(0.16)	(0.36)	(0.04)	(0.03)	(0.35)	(0.15)	(0.06)	(0.05)	(0.04)	(0.02)
LN(Board Size)	-0.145*	0.009	-0.011	0.003	0.017	0.051	-0.017	-0.008	0.001	-0.010
	(0.08)	(0.13)	(0.04)	(0.03)	(0.11)	(0.11)	(0.04)	(0.03)	(0.01)	(0.01)
MTB	0.108	-0.093	-0.131	-0.118	0.156	-0.022	-0.016	0.065	-0.127*	0.046
	(0.43)	(0.51)	(0.14)	(0.14)	(0.45)	(0.27)	(0.13)	(0.13)	(0.07)	(0.05)
ROA	-1.496	4.787	1.555	2.124**	1.108	-0.108	1.439***	0.843	0.338	0.258
	(1.80)	(3.96)	(1.05)	(0.88)	(4.10)	(1.06)	(0.55)	(0.54)	(0.25)	(0.21)
Q	-0.347	0.428	-0.190	0.540***	0.078	-0.200	0.161	-0.154	0.242*	0.073
	(0.76)	(0.84)	(0.25)	(0.20)	(0.72)	(0.41)	(0.20)	(0.23)	(0.14)	(0.06)
Size	0.117	0.009	-0.003	-0.018	0.030	-0.003	0.020	0.025	-0.025**	0.019**
	(0.08)	(0.11)	(0.03)	(0.02)	(0.12)	(0.03)	(0.03)	(0.02)	(0.01)	(0.01)
ZSCORE	0.005	0.007*	0.002	0.001	0.004	-0.003	-0.001	0.000	-0.000	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LN(Total Compensation)	0.015	-0.010	-0.006	0.003	-0.008	0.017	0.025	0.031*	0.006	-0.013
	(0.02)	(0.02)	(0.00)	(0.00)	(0.02)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)
Cash/TDC1	-0.036	0.271	0.012	-0.005	0.264	0.053	0.052	0.039	0.054***	-0.040
	(0.08)	(0.17)	(0.03)	(0.02)	(0.17)	(0.06)	(0.06)	(0.03)	(0.02)	(0.03)
Instrument:										
LN(CEO Age)	1.257***					1.620***				
	(0.27)					(0.35)				
Kleibergen-Paap rk Wald	21.50					22.04				
Regression	First Stage	IV	IV	IV	IV	First Stage	IV	IV	IV	IV
Observations	309	309	309	309	309	275	275	275	275	275
Fixed Effects	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year

4.5 Conclusion

In this paper, I examine how bank CEO debt incentives relate to bank liquidity creation. I find that higher CEO inside debt holdings are associated with lower bank liquidity creation. The results suggest that CEOs with higher inside debt adopt more conservative liquidity creation strategies. In addition, I find that the result is driven by large banks, suggesting that CEOs in large banks manage banks more conservatively than CEOs in small banks, as their inside debt holdings increase.

My results suggest that while regulators could increase bank liquidity creation by imposing lower CEO inside debt holding requirements, it could simultaneously make banks riskier, as Bennett, Guntay, and Unal (2015) and van Bekkum (2016) suggest. The results of my paper and previous studies, examining the relation between CEO inside debt and bank risk-taking, imply that debt-based compensation would be a double-edged sword for designing policy about bank liquidity creation and bank soundness. Also. The results suggest that regulators should design bank-specific policies regarding bank governance because, different from non-financial firms, banks can impact local markets and market participants.

Chapter 5:

Conclusion

The main focus of the first chapter is to investigate how CEOs communicate with the market through their trading pattern. Using a dataset of news articles collected from RavenPack, which has its own sentiment of news for every news story, I find that CEOs are more likely to purchase shares in the open market after positive and negative news release, suggesting that CEOs make the news salient through their trading pattern. Previous literature on insider trading focuses on insider trading pattern before the information releases and empirically shows that insider trading predicts stock returns and the information. The chapter contributes to the literature by exploring CEO trading pattern after the information reveals. Also, this chapter suggests that CEOs utilize the open market purchase as a tool of signaling.

In the second chapter, I exploit staggered state-level bank deregulation events in the United States as exogenous shocks in bank competition to examine the effects of bank competition on bank liquidity creation at the state level. My results show that state-level bank deregulation does not, on average, significantly affect state-level bank liquidity creation, while the bank deregulation decreases bank liquidity creation at the bank level. The chapter also contributes to the literature on the effects of bank deregulation on local economy. My results suggest that the positive effects of bank deregulation on local economic growth may not be driven by bank liquidity creation.

The third chapter examines bank CEO inside debt incentives and investigate whether bank CEO inside debt is associated with bank liquidity creation. My results show that CEO inside debt incentives increase bank liquidity creation, suggesting that bank CEOs adopt more conservative liquidity creation when they hold more inside debt. The results also suggest that while regulators could increase liquidity creation by imposing lower CEO inside debt requirements, it could simultaneously make banks riskier. This chapter contributes to policy debates on bank liquidity creation and bank soundness.

References

Agarwal, S., Driscoll, J. C., Gabaix, X., & Laibson, D. (2009). The age of reason: Financial decisions over the life cycle and implications for regulation. *Brookings Papers on Economic Activity*, *2009*(2), 51-117.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets*, *5*(1), 31-56.

Anantharaman, D., Fang, V. W., & Gong, G. (2013). Inside debt and the design of corporate debt contracts. *Management Science*, *60*(5), 1260-1280.

Bayazitova, D., & Shivdasani, A. (2011). Assessing tarp. *The Review of Financial Studies*, *25*(2), 377-407.

Bebchuk, L. A., Grinstein, Y., & Peyer, U. (2010). Lucky CEOs and lucky directors. *The Journal of Finance*, *65*(6), 2363-2401.

Bennett, R. L., Güntay, L., & Unal, H. (2015). Inside debt, bank default risk, and performance during the crisis. Journal of Financial Intermediation, 24(4), 487-513.

Berger, A. N., & Bouwman, C. H. (2009). Bank liquidity creation. *Review of Financial Studies*, *22*(9), 3779-3837.

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

Berger, A. N., Kick, T., & Schaeck, K. (2014). Executive board composition and bank risk taking. *Journal of Corporate Finance*, *28*, 48-65.

Berger, A. N., Klapper, L. F., & Turk-Ariss, R. (2009). Bank competition and financial stability. Journal of Financial Services Research, 35(2), 99-118.

Berger, A. N., & Roman, R. A. (2015). Did TARP banks get competitive advantages?. *Journal of Financial and Quantitative Analysis*, *50*(6), 1199-1236.

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

Bertrand, M., & Mullainathan, S. (2003). Enjoying the quiet life? Corporate governance and managerial preferences. *Journal of political Economy*, *111*(5), 1043-1075.

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

Black, S. E., & Strahan, P. E. (2002). Entrepreneurship and bank credit availability. *The Journal of Finance*, *57*(6), 2807-2833.

Boyd, J. H., & De Nicolo, G. (2005). The theory of bank risk taking and competition revisited. *The Journal of finance*, *60*(3), 1329-1343.

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

Bushee, B. J. (2001). Do institutional investors prefer near-term earnings over long-run value?. *Contemporary Accounting Research*, *18*(2), 207-246.

Bushee, B. J., & Miller, G. S. (2012). Investor relations, firm visibility, and investor following. *The Accounting Review*, *87*(3), 867-897.

Bushee, B. J., Core, J. E., Guay, W., & Hamm, S. J. (2010). The role of the business press as an information intermediary. *Journal of Accounting Research*, *48*(1), 1-19.

Bushman, R. M., Williams, C. D., & Wittenberg-moerman, R. (2017). The informational role of the media in private lending. *Journal of Accounting Research*, *55*(1), 115-152.

Cassell, C. A., Huang, S. X., Sanchez, J. M., & Stuart, M. D. (2012). Seeking safety: The relation between CEO inside debt holdings and the riskiness of firm investment and financial policies. *Journal of Financial Economics*, *103*(3), 588-610.

Cetorelli, N., & Strahan, P. E. (2006). Finance as a barrier to entry: Bank competition and industry structure in local US markets. *The Journal of Finance*, *61*(1), 437-461.

Chang, X., Fu, K., Low, A., & Zhang, W. (2015). Non-executive employee stock options and corporate innovation. *Journal of financial economics*, *115*(1), 168-188.

Chava, S., Kumar, P., & Warga, A. (2009). Managerial agency and bond covenants. *The Review of Financial Studies*, *23*(3), 1120-1148.

Chava, S., Oettl, A., Subramanian, A., & Subramanian, K. V. (2013). Banking deregulation and innovation. *Journal of Financial Economics*, *109*(3), 759-774.

Choi, S. (2019). Does Bank Competition Increase Bank Liquidity Creation? A State-level Perspective.

Coles, J. L., Daniel, N. D., & Naveen, L. (2013). Calculation of compensation incentives and firm-related wealth using Execucomp: Data, program, and explanation.

Core, J. E., Guay, W., & Larcker, D. F. (2008). The power of the pen and executive compensation. *Journal of financial economics*, *88*(1), 1-25.

Cornaggia, J., Mao, Y., Tian, X., & Wolfe, B. (2015). Does banking competition affect innovation?. *Journal of financial economics*, *115*(1), 189-209.

Dai, L., Parwada, J. T., & Zhang, B. (2015). The governance effect of the media's news dissemination role: Evidence from insider trading. *Journal of Accounting Research*, *53*(2), 331-366.

Deep, A., & Schaefer, G. (2004). Are banks liquidity transformers? (No. rwp04-022).

DeYoung, R., & Huang, M. (2016). The External Effects of Bank Executive Pay: Liquidity Creation and Systemic Risk.

Diamond, D. W., & Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. *The journal of political economy*, 401-419.

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

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.

Dyck, A., Volchkova, N., & Zingales, L. (2008). The corporate governance role of the media: Evidence from Russia. *The Journal of Finance*, *63*(3), 1093-1135.

Dyck, A., Morse, A., & Zingales, L. (2010). Who blows the whistle on corporate fraud?. *The Journal of Finance*, *65*(6), 2213-2253.

Fahlenbrach, R., & Stulz, R. M. (2011). Bank CEO incentives and the credit crisis. *Journal of financial economics*, *99*(1), 11-26.

Fang, L., & Peress, J. (2009). Media coverage and the cross-section of stock returns. *The Journal of Finance*, *64*(5), 2023-2052.

Fidrmuc, J. P., Goergen, M., & Renneboog, L. (2006). Insider trading, news releases, and ownership concentration. *The Journal of Finance*, *61*(6), 2931-2973.

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.

Gorton, G., & Pennacchi, G. (1990). Financial intermediaries and liquidity creation. *The Journal of Finance*, *45*(1), 49-71.

Greene, W. (2004). The behaviour of the maximum likelihood estimator of limited dependent variable models in the presence of fixed effects. *The Econometrics Journal*, *7*(1), 98-119.

Hellmann, T. F., Murdock, K. C., & Stiglitz, J. E. (2000). Liberalization, moral hazard in banking, and prudential regulation: Are capital requirements enough? *American economic review*, 147-165.

Heron, R. A., & Lie, E. (2007). Does backdating explain the stock price pattern around executive stock option grants?. *Journal of Financial Economics*, *83*(2), 271-295.

Holmström, B., & Tirole, J. (1998). Private and public supply of liquidity. *Journal of political Economy*, *106*(1), 1-40.

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

Huberman, G., & Regev, T. (2001). Contagious speculation and a cure for cancer: A nonevent that made stock prices soar. *The Journal of Finance*, *56*(1), 387-396.

Jayaratne, J., & Strahan, P. E. (1996). The finance-growth nexus: Evidence from bank branch deregulation. *The Quarterly Journal of Economics*, *111*(3), 639-670.

Jeng, L. A., Metrick, A., & Zeckhauser, R. (2003). Estimating the returns to insider trading: A performance-evaluation perspective. *Review of Economics and Statistics*, *85*(2), 453-471.

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of financial economics*, *3*(4), 305-360.

Jenter, D. (2005). Market timing and managerial portfolio decisions. *The Journal of Finance*, *60*(4), 1903-1949.

Jiang, L., Levine, R., & Lin, C. (2019). Competition and bank liquidity creation. *Journal of Financial and Quantitative Analysis*, 1-50.

Joe, J. R., Louis, H., & Robinson, D. (2009). Managers' and investors' responses to media exposure of board ineffectiveness. *Journal of Financial and Quantitative Analysis*, *44*(3), 579-605.

Joh, S. W., & Kim, J. (2008). Does Competition Affect the Role of Banks as Liquidity Providers? *Seoul National University*.

Johnson, C. A., & Rice, T. (2008). Assessing a decade of interstate bank branching. *Wash. & Lee L. Rev.*, *65*, 73.

Karolyi, G. A., & Liao, R. C. (2017). The economic consequences of investor relations: A global perspective. *Available at SSRN 2591079*.

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.

Ke, B., Huddart, S., & Petroni, K. (2003). What insiders know about future earnings and how they use it: Evidence from insider trades. *Journal of Accounting and Economics*, *35*(3), 315-346.

Keeley, M. C. (1990). Deposit insurance, risk, and market power in banking. *American economic review*, *80*(5), 1183-1200.

Kirk, M. P., & Vincent, J. D. (2014). Professional investor relations within the firm. *The Accounting Review*, *89*(4), 1421-1452.

Koetter, M., Kolari, J. W., & Spierdijk, L. (2012). Enjoying the quiet life under deregulation? Evidence from adjusted Lerner indices for US banks. *Review of Economics and Statistics*, *94*(2), 462-480.

Kolasinski, A., & Li, X. (2010). Are corporate managers savvy about their stock price? Evidence from insider trading after earnings announcements. *Journal of Accounting and Public Policy*, *29*(1), 27-44.

Kovalchik, S., Camerer, C. F., Grether, D. M., Plott, C. R., & Allman, J. M. (2005). Aging and decision making: A comparison between neurologically healthy elderly and young individuals. *Journal of Economic Behavior & Organization*, *58*(1), 79-94.

Krishnan, K., Nandy, D. K., & Puri, M. (2014). Does financing spur small business productivity? Evidence from a natural experiment. *The Review of Financial Studies*, *28*(6), 1768-1809.

Kroszner, R. S., & Strahan, P. E. (1999). What drives deregulation? Economics and politics of the relaxation of bank branching restrictions. *The Quarterly Journal of Economics*, *114*(4), 1437-1467.

Kuhnen, C. M., & Niessen, A. (2012). Public opinion and executive compensation. Management Science, 58(7), 1249-1272.

Lakonishok, J., & Lee, I. (2001). Are insider trades informative?. *The Review of Financial Studies*, *14*(1), 79-111.

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

Lie, E. (2005). On the timing of CEO stock option awards. *Management Science*, *51*(5), 802-812.

Mian, A., Sufi, A., & Trebbi, F. (2010). The political economy of the US mortgage default crisis. *American Economic Review*, *100*(5), 1967-98.

Miller, G. S. (2006). The press as a watchdog for accounting fraud. *Journal of Accounting Research*, *44*(5), 1001-1033.

Petersen, M. A., & Rajan, R. G. (1994). The benefits of lending relationships: Evidence from small business data. *The journal of finance*, *49*(1), 3-37.

Petersen, M. A., & Rajan, R. G. (1995). The effect of credit market competition on lending relationships. *The Quarterly Journal of Economics*, *110*(2), 407-443.

Peress, J. (2014). The media and the diffusion of information in financial markets: Evidence from newspaper strikes. *The Journal of Finance*, *69*(5), 2007-2043.

Phan, H. V. (2014). Inside debt and mergers and acquisitions. *Journal of Financial and Quantitative Analysis*, *49*(5-6), 1365-1401.

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

Rice, T., & Strahan, P. E. (2010). Does Credit Competition Affect Small-Firm Finance?. *The Journal of Finance*, *65*(3), 861-889.

Rogers, J. L., Skinner, D. J., & Zechman, S. L. (2016). The role of the media in disseminating insider-trading news. *Review of Accounting Studies*, *21*(3), 711-739.

Schaeck, K., Cihak, M., & Wolfe, S. (2009). Are competitive banking systems more stable? *Journal of Money, Credit and Banking*, *41*(4), 711-734.

Seyhun, H. N. (1986). Insiders' profits, costs of trading, and market efficiency. *Journal of financial Economics*, *16*(2), 189-212.

Sivakumar, K., & Waymire, G. (1994). Insider trading following material news events: Evidence from earnings. *Financial Management*, 23-32.

Solomon, D. H., & Soltes, E. F. (2012). Managerial control of business press coverage. *Available at SSRN 1918138*.

Srivastav, A., Armitage, S., & Hagendorff, J. (2014). CEO inside debt holdings and risk-shifting: Evidence from bank payout policies. *Journal of Banking & Finance*, *47*, 41-53.

Stiglitz, J. E., & Weiss, A. (1981). Credit rationing in markets with imperfect information. *The American economic review*, *71*(3), 393-410.

Sundaram, R. K., & Yermack, D. L. (2007). Pay me later: Inside debt and its role in managerial compensation. *The Journal of Finance*, *62*(4), 1551-1588.

Van Bekkum, S. (2016). Inside debt and bank risk. *Journal of Financial and Quantitative Analysis*, *51*(2), 359-385.

Wang, Y., Zhang, B., & Zhu, X. (2017). The Momentum of News. Available at SSRN 3267337.

Wei, C., & Yermack, D. (2011). Investor reactions to CEOs' inside debt incentives. *The Review of Financial Studies*, *24*(11), 3813-3840.

Yim, S. (2013). The acquisitiveness of youth: CEO age and acquisition behavior. *Journal of financial economics*, *108*(1), 250-273.