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ESSAYS ON STABILITY AND REGULATION OF THE BANKING SYSTEM

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ABSTRACT

This dissertation consists of three chapters each of which explores different topics in the area of banking. In the first chapter, I ask how a bank's connectedness affects its financial stability and what mechanisms amplify or mitigate this effect. I consider connectedness arising due to linkages that are formed between banks when they are exposed to common housing markets, and investigate whether such connectedness explains stability around the 2007 housing crash. I show that linkages facilitate contagion of risk, and that high leverage and securitization activity of other banks amplify contagion while high liquidity ratio of other banks minimizes contagion. Finally, I provide policy implications by suggesting minimum levels of capital and liquidity ratios that could contain contagion.

In the second chapter, I study the impact of a newly introduced liquidity requirement in the banking sector – the Liquidity Coverage Ratio (LCR) rule – on loan contract terms. This chapter employs a differences-in-differences testing method, and exploits the setting of multiple events arising from the timing of the implementation of the rule to identify the effect of LCR. I do not find evidence of high costs to lenders due to this rule, because loan pricing terms do not change in an average loan post LCR. However, banks limit their risk exposure by increasing collateral requirements. For banks that are ex-ante expected to find the rule less costly, I find evidence of cost savings because they offer lower spreads. Further results suggest that while banks provided extra benefits to relationship borrowers in the form of lower spreads pre LCR, this is no longer true post LCR, and they reduce risk exposure to borrowers with weaker relationship strength by increasing collateral requirements.

In the third chapter, I study the relationship between liquidity created by a bank and its overall financial stability. I contrast results during the period of 2007 financial crisis with those during normal times. While I find that overall liquidity creation is a risky activity during both times, breaking it into different components (on- vs. off-balance sheet, asset side vs. liability side) reveals nuances on the driving forces behind this relationship. While asset side liquidity creation decreases stability during both times, results show that the effects of other components depend on overall market conditions. During the crisis period, off-balance sheet liquidity creation hurts stability, while it has no apparent benefit during normal times. Liability side liquidity creation improves stability during crisis, however there is evidence of costs of such activity during normal times. Further results show that liquid holdings and core deposits can mitigate the costs of liquidity creation during crisis without significantly hurting benefits during normal times.

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PREFACE

The second chapter is based on work that is coauthored with Jess Cornaggia.

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Chapter 1

Interbank Connections and Financial Stability

1.1 Introduction

In the wake of the 2007 financial crisis, governments around the globe convened to coordinate their efforts to manage the fallout of the crisis. At the forefront of these efforts were ways to address the intertwined structure of the banking system – a structure that is characterized by interbank connections or linkages that facilitate contagion. The aftermath of the crisis also underscored negative consequences of such structure on the real economy. In response, the Basel Committee took several initiatives, one of which was a framework of higher capital standards for Global Systemically Important Banks (GSIB). As Yellen (2013) notes, indicators of connectedness accounted for a significant portion of the overall score that determined whether an institution should be subject to higher requirements.[1]

Given the attention that the issue of connectedness has received in recent years, I first ask how a bank's connectedness is related to its financial stability, and investigate whether such connectedness leads to contagion of risk from one bank to another. Second, I ask if there are mechanisms that amplify or mitigate the magnitude of the relationship between connectedness and stability. In particular, I consider a bank's exposure to leverage, securitization activity and liquid holdings of *other* banks as potential mechanisms that affect this relationship.

Recently, there has been a surge in theoretical and empirical work to study the link between connectedness and stability. However, Glasserman and Young (2016), in a

[1] See Bank of International Settlements (2009).

survey on the extant literature in the area, argue that existing empirical work has not produced a convincing link between the two. Many empirical papers have studied spillover effects from one bank to another by studying direct linkages such as those arising due to interbank lending. However this approach is challenging given that data on bilateral loan exposures are not publicly available, and such data are needed to construct linkages between banks.[2] As Upper (2011) notes, many researchers studying these linkages have, therefore, resorted to estimating bilateral exposures from aggregate data and simulating spillover effects.

This paper attempts to fill the gap in the literature by considering a novel setting of indirect linkages, one that allows a purely empirical study of the impact of interbank connections on financial stability. The linkages that I consider are the ones that arise between banks when they are exposed to common housing markets. There are multiple phenomena of contagion that give rise to indirect linkages such as information contagion (spread of fear of losses leading investors to run on banks), contagion through common asset holdings (Allen, Babus, and Carletti (2012)), and contagion through common regulation (Morrison and White (2013)).[3] Exposure to common housing markets is one such phenomenon, and is clearly an important one given that the 2007 financial crisis was initiated by troubles in the housing industry.[4]

Under this setting, I construct linkages between banks using publicly available Home Mortgage Disclosure Act (HMDA) database. This database provides data on home loan originations and information on geographic location of properties. I use this loan origination and location information to determine whether banks overlap in a housing

[2] For example, in the study of interbank linkages, information on aggregate amounts lent and borrowed by a bank is available, but details on who the amounts are lent to/borrowed from are not public information.
[3] See literature review (section II) for further description of these contagion phenomena.
[4] A strand of empirical literature studies indirect connectedness due to stock return correlations. See Section II for a description of this literature and a discussion on how this paper differs from that literature.

market, represented by a Metropolitan Statistical Area (MSA), and define linkages between them if they do.[5,6]

One possible mechanism of contagion in this setting is through common collateral holdings. For example, consider how, in a given MSA, the riskiness of bank A could increase due to spillover effects from other banks that are distressed by a shock, even though bank A is otherwise safe. In the event of a large shock, distressed banks contract lending (see Dagher and Kazimov (2015)).[7] If no other bank is able to pick up the slack – as is likely in the event of a large shock – local housing activity declines. Decline in housing activity accelerates the decline in home prices initiated by the shock (see Favara and Imbs (2015), Rajan and Ramcharan (2016)).[8] As a result, bank A suffers further declines in the value of the collateral it holds, and its credit exposure increases.[9]

While such interbank connections can subject a bank to contagion in the event of a large shock, if they correspond to a more diversified pattern of lending, it is also possible that they have a positive impact on the stability of the bank. For example, in the setting considered here, banks form new linkages when they originate loans in new geographic regions. If doing so helps them diversify their geographic risk exposure, they

[5] MSAs are geographic areas consisting of a core area of at least 50,000 population and adjacent counties that have close social and economic ties with the core (as measured by commuting ties). The Census bureau delineates these areas for statistical purposes.

[6] I only use portfolio loans (loans that are not sold during the given calendar year) to determine if banks overlap in a market. See section IV.

[7] Dagher and Kazimov (2015) use the HMDA database to show that mortgage application rejection rates increased (i.e., banks contracted lending) during the 2007 housing crisis.

[8] Favara and Imbs (2015) use the HMDA database to show that increases in mortgage lending lead to increases in home prices. Similarly, Rajan and Ramcharan (2016) find that reduction in local financial intermediation capacity depresses local land prices, and results in distress in nearby banks.

[9] Another possible mechanism of contagion from *other* banks to bank A is through information contagion. In this case, investors are fearful of spread of risk following increased distress at other banks (see Allen, Babus, and Carletti (2012)), and thus are wary of availing funds not just to those distressed banks, but also to bank A. Therefore, investors will increase funding costs not only for distressed banks, but also for bank A. Banks will then pass down increased funding costs to borrowers, thus leading to a lower housing demand. Such decline in housing demand puts a further downward pressure on home prices and affects bank A's credit exposure. Such effect on home prices due to increased funding costs and through borrower demand channel is formalized in Goel, Song, and Thakor (2014).

could benefit from these linkages. How interconnections affect stability is ultimately an empirical question.

With linkages defined as above, I can now view all banks as being in a network, in which they are connected to one another through these linkages. So, I employ a network-based approach to construct a measure of connectedness for each bank. Specifically, I construct a measure called eigenvector centrality, which is a ranking variable that assigns high scores to highly connected banks. I construct this measure such that the score for each bank is proportional to (a) its loan exposure to other banks, and (b) the connectedness of *other* banks.[10] This measure, thus, captures vulnerability of a bank to contagion occurring from other banks.

I then conduct an event study around the 2007 housing crash, and ask how a bank's connectedness during pre-crisis affects its stability during crisis. My primary measure for bank stability is a commonly used measure called z-score, which captures a bank's distance to default.[11] The 2007 housing crash was a shock of substantial magnitude and is relevant to the type of linkage that I consider. I find that having higher centrality during pre-crisis makes a bank riskier during crisis, and this result is statistically and economically significant. I find that an increase in centrality of an average bank from 25th to 50th percentile decreases its stability by 3.5%. I further show that this negative relationship between centrality and stability is due to contagion of distress occurring from other banks to the subject bank. For example, I show that the riskiness of the subject bank increases only when I consider its linkages to highly risky banks, but not when I consider its linkages to stable banks.

Next, I investigate mechanisms that magnify or mitigate the magnitude of contagion through interbank connections. First, I consider leverage of *other* banks as a contagion-amplifying mechanism. The underlying intuition comes from the idea that highly levered banks are less capable of absorbing negative shocks, and thus amplify the initial impact of the shock. This amplified shock is then transmitted to other banks through linkages. I find results that are consistent with this idea: For a bank that is

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[10] This measure is described in detail in section V.
[11] See section V for a description of z-score.

connected with banks having low leverage, an increase in centrality from 25th to 50th percentile implies a decline of 3.0% in stability, while a similar increase in centrality of a bank connected with highly levered banks results in a 28.2% decline in stability.

I then consider securitization activity of other banks as another contagion-amplifying mechanism. The securitization market expanded substantially prior to the 2007 crisis, and many studies have linked such expansion in securitization activity to deterioration in loan quality and to the onset of the crisis. To the extent that securitization leads to origination of poor quality loans, when the secondary market freezes, banks involved in greater degree of securitization activity are stuck with poorer quality loans.[12] These banks should, therefore, be affected to a greater extent by the shock, thereby amplifying the magnitude of the initial shock and thus the following spillover effect. My results show that the securitization activity of other banks indeed leads to a magnified contagion effect.

Finally, I consider liquid holdings ratio of other banks as a contagion-mitigating mechanism. Liquid holdings absorb the negative effects of shocks, and they decrease the need to fire-sell assets that would otherwise have spillover effects on other banks. The events of the crisis highlighted the importance of holding liquid assets, and in response, the Federal Reserve introduced new liquidity requirements. I find that high liquid holdings ratio by other banks indeed mitigate the magnitude of contagion.

Several robustness tests support these results. A placebo test around a false crisis event provides evidence that my results are indeed triggered by the shock of the 2007 housing crash.[13] Moreover, a test using placebo linkages provides evidence that the mechanism behind the construction of linkages drives my results. Further tests show that my results are not due to common market conditions and that these results do not change if loan sales break linkages. Results are also robust to using alternate dependent and independent variables.

[12] During the crisis period, the non-agency secondary market froze. While the Fannie Mae and Freddie Mac were still purchasing loans, during the beginning of 2007, the Freddie Mac announced that it would no longer buy subprime loans, indicating increasing difficulty in loan sales even in the agency market.

[13] False crisis is the two-year time period immediately preceding the 2007 crisis. See section VI.

These findings on how interconnections facilitate contagion and what mechanisms amplify or mitigate the magnitude of contagion can inform policymakers in developing better ways to contain contagion. I also provide specific policy implications by suggesting minimum levels of capital and liquid holdings ratios that could contain the spread of risk. In particular, I find that banks having Tier 1 risk based capital ratio greater than 12.5% and banks having liquid holdings ratio greater than 18.4% did not contribute in contagion, thus suggesting that these levels could prevent contagion through linkages.[14,15]

The rest of the paper is organized as follows. Section II reviews related literature, section III develops hypotheses, section IV describes data, and section V discusses methods. Section VI discusses the main results of the paper, while section VII performs robustness tests. Section VIII discusses policy implications, and, finally, section IX concludes.

1.2 Literature Review

There are two broad areas of the literature that studies the relationship between interbank connections and stability – one studies direct linkages while the other studies indirect linkages (Kara and Tian (2015)). This section provides a brief overview of those two areas in turn.

Early theory in the area of direct linkages includes Allen and Gale (2000) and Freixas, Parigi, and Rochet (2000), who study linkages arising due to interbank lending. In these papers, a highly connected network corresponds to a well-diversified pattern of lending such that a connected system enhances stability.[16] In contrast, Brusco and

[14] The capital ratio used in this paper is the one that was implemented by the Federal Reserve during the pre-crisis period. See section V for more description of this ratio.

[15] The newly implemented liquidity requirements are different from the liquid holdings ratio that I study here. (New policies require banks to hold enough liquid assets to withstand a stress scenario.) Section V describes how I compute this ratio.

[16] In Allen and Gale (1999), banks lend to one another in different regions because the liquidity shocks faced by banks in these regions are imperfectly correlated, and such diversified lending allows them to

Castiglionesi (2007) modify Allen and Gale (2000) to include moral hazard; they argue that risk diversification benefits of interconnections incentivize banks to take higher risks. Such risk taking leads to a more fragile financial system. Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015), on the other hand, argue that connectedness leads to a "robust-but-fragile" network: As long as the magnitude of the shock is below a certain cut-off point, interconnections enhance stability. Beyond that point, they facilitate contagion.

Several theory papers shed light on various mechanisms that amplify the contagion effect of interconnections. Rogers and Veraart (2013) highlight the role of bankruptcy costs and asset recovery rates in magnifying contagion, Cifuentes, Ferrucci, and Shin (2005) highlight fire sale of commonly held assets, and Glasserman and Young (2015) highlight size, leverage, asset quality, and loss of confidence in the creditworthiness of financial institutions.[17]

As noted earlier, empirical literature that studies direct linkages is limited to simulation methods due to lack to publicly available data. Upper (2011) surveys papers that use these methods to study contagion in interbank lending markets in different countries (e.g. Furfine (2003) in U.S, Upper and Worms (2004) in Germany, Amundsen and Arnt (2005) in Denmark, Degryse and Nguyen (2007) in Belgium). These papers do not find economically significant evidence of contagion. Elsinger, Lehar, and Summer (2006) argue that while contagion in interbank market is rare, it could have a sizable negative impact if it does happen. Gai, Haldane, and Kapadia (2011), on the other hand, find that increasing connectedness first increases and then decreases the probability of a

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insure against shocks ex-ante. But such lending exposes banks to greater counterparty risk in the event of an unexpected negative shock. The paper compares complete versus ring network. A complete network, in which every bank lends to every other bank, is more stable since losses from a distressed bank are divided among all others, while a ring network, in which each bank borrows from exactly one other bank, is fragile since losses are concentrated on only one other bank. In Freixas, Parigi, and Rochet (2000), banks face liquidity shocks due to migration of depositors and interbank lending helps reduce costs of early withdrawals due to such migration. This paper also compares complete and ring networks and arrive at conclusions that are similar to Allen and Gale (1999).

[17] These papers build on the theoretical framework of Eisenberg and Noe (2001), who provide a basic network based model for transmission of defaults from one node to another.

funding crisis; however, the severity of crisis, conditional on the occurrence of a crisis, always increases.

Empirical work studying direct linkages has also investigated linkages due to CDS exposures. For example, Markose, Giansante, and Shaghaghi (2012) use estimates of bilateral CDS exposures and simulate transmission of losses, while Morrison et al. (2017) document correlations in CDS profits of connected banks.

In the area of indirect linkages, Allen, Babus, and Carletti (2012) provide a theory of linkages arising due to common asset holdings. They argue that a greater degree of asset commonality increases information contagion and the likelihood of systemic risk.[18] Another theory in the area is Morrison and White (2013), who contend that banks can be linked due to common regulation – the failure of a bank leads investors to lose confidence in the bank's regulator, and such loss of confidence in the regulator causes investors to further lose confidence in other banks chartered by the same regulator.

A strand of empirical literature uses equity return correlations to construct indirect linkages between banks (e.g., Billio et al. (2012), Diebold and Yılmaz (2014)). In this setting, several mechanisms could be responsible for such linkages – it could be common asset holdings, common market exposures, or interbank lending. My paper is different from this literature in that it focusses on one particular mechanism of contagion – the one that facilitates contagion through an impact on home prices in a common housing market. Other empirical work on indirect linkages has studied linkages due to common portfolio holdings as in Greenwood, Landier, and Thesmar (2015), who employ a simulation method to document spillover effects.

Finally, my paper is related to Iyer and Peydró (2011), who study spillover effects following the failure of a large Indian bank. They find large withdrawal of deposits and declines in profits in banks that have high exposure to the failed bank. In my paper,

[18] The source of systemic risk in Allen, Babus, and Carletti (2012) is the investors' decision on whether to roll over debt. When investors do not roll over debt, banks are forced to liquidate projects. The authors argue that this decision depends on the structure of the network pattern. Investors are more likely to not roll over debt in a clustered network, in which all banks hold the same portfolio, compared to an unclustered network, in which all banks hold different portfolios. This is because the probability of a rash of defaults is lower in an unclustered network.

however, I study spillover of risk. Furthermore, I explore how different characteristics of *other* banks affect the stability of the subject bank. Such study is not possible in the setting of Iyer and Peydró (2011) given that there is only one source of distress – the large bank that fails.

1.3 Hypotheses

This section outlines the main hypotheses of my paper. The first hypothesis concerns the relationship between connectedness and stability of a bank. Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015) emphasize the importance of the magnitude of a negative shock in the study of this relationship. They consider linkages due to interbank lending and argue that if the magnitude of the shock is below a certain threshold, a densely connected network, corresponding to a diversified pattern of lending, improves stability. However, if the magnitude of the shock crosses the threshold, these linkages facilitate contagion of distress, thus decreasing stability. Following this intuition, I test the impact of interconnections on bank stability around the 2007 housing crash, which was a shock of substantial magnitude. As per theory, high connectedness of banks during the pre-crisis period should result in greater instability during the crisis period. Therefore, hypothesis I is as follows:

Hypothesis 1: Higher connectedness during pre-crisis decreases stability during crisis by facilitating contagion of risk.

Next, I am interested in mechanisms that amplify or mitigate the effect of connectedness on stability. Hypothesis 2 concerns leverage of other banks as a possible contagion-magnifying mechanism. Since highly levered banks are not capable of absorbing shocks, they amplify the initial effect of the shock, thus leading to an amplified contagion effect. The motivation for this comes from Goel, Song, and Thakor (2014), who argue that a bank's credit exposure increases with leverage choices of other banks.[19] Similarly, Glasserman and Young (2015) suggest that spillover effects are stronger when they originate at banks with high leverage. Therefore, the second hypothesis is as follows:

Hypothesis 2: High leverage of *other* banks amplifies the contagion effect of interconnections.

My third hypothesis considers securitization activity of other banks as another contagion-amplifying mechanism. Purnanandam (2011) finds evidence that securitization leads to reduced ex ante screening of borrowers and excessive origination of poor-quality mortgages. Similarly, Loutskina (2011) finds that securitization leads to excessive lending and reduction in liquid asset holdings, and thus argues that it makes banks more vulnerable if the secondary market shuts down. The non-agency secondary market did shut down during crisis, and the government sponsored entities stopped buying subprime loans. To the extent that securitization leads to poor quality loans and banks are stuck with these during crisis, the initial effect of the shock should be amplified in banks that are involved in greater degree of securitization activity, thus leading to a magnified contagion effect. Hypothesis 3 is as follows:

Hypothesis 3: High securitization activity of *other* banks amplifies the contagion effect of interconnections.

Finally, my fourth hypothesis concerns the contagion-mitigating effect of liquid holdings of other banks. Since banks holding high amounts of liquid assets are capable of absorbing shocks, the initial effect of the shock is mitigated at these banks, such that the

[19] Goel, Song, and Thakor (2014) argue that because highly levered banks are less capable of absorbing negative shocks, there is a greater increase in fund-raising costs for these banks, leading them to supply credit at higher costs. This further results in lower loan demand, which accelerates the decrease in home prices initiated by the shock. Such decline in home prices then increases the otherwise independent bank's credit risk exposure.

resulting contagion effect is also diminished. Stein (2013) argues that the lack of liquid assets increases the risk of run, and leads banks to contract lending and fire-sell illiquid assets. Fire-sale of assets has further spillover effects on other banks. Cifuentes, Ferrucci, and Shin (2005) model fire sale as a mechanism that magnifies contagion in an interbank lending network, and suggest that liquid buffers can help mitigate contagion. Therefore, contagion should be mitigated if they originate at banks that hold high amounts of liquid assets. Hypothesis 4 is as follows:

Hypothesis 4: High liquid holdings of *other* banks mitigate the contagion effect of interconnections.

1.4 Data

I use two sources of data in this paper – Home Mortgage Disclosure Act (HMDA) database for detailed loan level information, and the call report database for bank balance sheet information. Congress enacted HMDA in 1975 to improve public reporting of mortgage loans.[20] US financial institutions are required to report HMDA data to their regulators if they meet certain criteria, such as having assets beyond some threshold.[21,22] This is an annual database and contains information on loan applications (regardless of

[20] This law was enacted to ensure that lenders were serving the housing needs of their communities in an indiscriminatory way.

[21] Any depository institution that has a home office or branch in an MSA is required to file HMDA if it has made a home purchase loan on a one-to-four unit dwelling or has refinanced a home purchase loan, and has assets above an annually adjusted threshold. Every December, the Consumer Financial Protection Bureau announces the threshold for the following year. For example, in 2007, this threshold was $36 million. Any non-depository institution (e.g., a mortgage company that does not accept deposits but raises funds for lending by borrowing from banks or capital markets) is required to file if at least 10% of its loan portfolio is composed of home purchase loans, and if it holds assets exceeding $10 million (Dell'Ariccia, Igan, and Laeven (2012)).

[22] Although lenders with offices only in non-metropolitan areas are exempt from filing HMDA, as Dell'Ariccia, Igan, and Laeven (2012) note, 82.6% of the population in 2000 and 83.2% of the population in 2006 lived in metropolitan areas, such that the data in HMDA are well representative of the residential mortgage lending activity in the U.S.

whether or not they were approved), borrower demographics, lender details, and loan specifics such as loan amount and geographic location of the property. This database provides a comprehensive coverage of the mortgage market. For example, Avery et al. (2010) note that in 2008, commercial banks filing HMDA carried 93% of the total mortgage dollars outstanding on commercial bank portfolios at the time.

For this paper, I obtain a subsample of loans that were originated between 2005 and 2009, which are the years surrounding the housing crisis. I filter for loans that are (i) not guaranteed by FHA/VA/FmHA, (ii) not sold (as of the calendar year-end) or sold to an affiliate, and (iii) have loan amounts greater than $50,000. Note that loans that are originated to be sold are usually immediately sold within few months. Since these loans are not sold within a given calendar year end, they represent portfolio lending (see Berrospide, Black, and Keeton (2016)).

I supplement this subsample from the HMDA database with lender details from the HMDA Lender file[23]. This file matches every lender who has filed a HMDA report on and after 1993 with the identification code (RSSD) used by the Federal Reserve Board. If the HMDA lender is a subsidiary of another bank or thrift, the lender file matches the filer to its parent company. If the lender is a subsidiary of a bank holding company, the file matches the lender to the lead/largest bank of the holding company. In cases where a HMDA lender is merged into another institution, the lender is matched with the acquiring institution. I only keep commercial banks, savings banks, and savings and loans associations in my sample. If applicable, I match these banks in my sample to the highest bank holding companies provided in the Call Reports database (described below). All independent banks and bank holding companies will be referred to as “banks” from here on.

The next database I use is the call report database (Report of Condition and Income), which provides detailed information on a bank’s income statement, balance-sheet items and off-balance-sheet activities. All financial institutions regulated by the Federal Reserve System, Federal Deposit Insurance Corporation (FDIC), and the

[23] I thank Robert Avery at Federal Housing Finance Agency (FHFA) for providing me with this file.

Comptroller of Currency are required, on a quarterly basis, to file these reports. These reports are publicly available through Federal Reserve Bank of Chicago (and can be obtained from Wharton Research Data Services (WRDS)).

After obtaining data from all of these sources, my sample has a total of 1348 unique banks. I also split my sample into large and small banks to study differential responses of the two size classes. Large banks are banks having gross total assets or GTA (total assets plus allowance for loan and lease losses plus the allocated transfer risk reserve) exceeding \$1 billion and small banks are those having up to \$1 billion GTA.[24] The final sample has 359 large banks and 989 small banks.

1.5 Methods

1.5.1 Model

In this paper, I use the 2007 housing crash as a shock that distresses banks, and conduct a test around this event to study how connectedness affects stability. Specifically, I test whether connectedness of a bank during the pre-crisis period (2005-2006) decreases the stability of the bank during the crisis period (2007-2009). I use the following OLS regression model:

$$Y_i = \alpha + \beta_1 Connectedness_i + B\ Control\ Variables_i \qquad (1)$$

where Y_i is bank i's measure of stability during crisis and $Connectedness_i$ is bank i's measure of connectedness (described in the next subsection) during pre-crisis. All control variables, along with the main independent variable, are averaged over the pre-crisis period. I perform a cross-sectional regression with robust standard errors.

In addition, I consider an alternate model in which I ask whether connectedness explains a high decline in stability from pre-crisis to crisis. I say that a bank undergoes a

[24] I follow Berger and Bouwman (2013) in defining GTA.

high decline in stability if any percent decline in stability from pre-crisis to crisis is larger than the median for the sample. Then, I study whether the probability of a high decline in stability increases as connectedness of a bank increases. I specify the following probit model:

$$high\ decline\ in\ \mathrm{Y}_i = \alpha + \beta_1 Connectedness_i + B\ Control\ Variables_i \qquad (2)$$

where *high decline in* Y_i is a dummy variable taking the value 1 if the bank undergoes a high decline in stability from pre-crisis to crisis.

In order to study mechanisms that amplify or mitigate the contagion effect of interconnections, I use the following specification:

$$\begin{aligned} Y_i = {} & \alpha + \beta_1\ Connectedness_i + \beta_2 Amplifier_i \qquad (3) \\ & + \beta_3\ Connectedness_i\ X\ Amplifier_i + B\ Control\ Variables_i \end{aligned}$$

where Y_i is the measure for stability (in the OLS model) or the dummy variable identifying a high decline in stability (in the probit model). $Amplifier_i$ is weighted average leverage, securitization activity, or liquid holdings of *other* banks with which bank *i* is connected (described below). The variable of interest here is the interaction term.

1.5.2 Variables

a) Network Centrality

In order to measure connectedness of a bank, I borrow the concept of eigenvector centrality from the networks literature. This measure is a ranking variable, which gives high scores to banks whose linkages themselves are highly connected. By accounting for connectedness of linkages, this variable appeals to the intuition that connectedness of a bank is not only determined by banks that are one degree apart, but also those that are more than one degree apart. Specifically, an eigenvector centrality of a bank is a score that is proportional to centralities of other banks with which it is connected (see Jackson (2008), Larcker, So, and Wang (2013)):

$$\lambda \cdot Centrality_i = \sum_j g_{ij} \cdot Centrality_j, \tag{4}$$

where λ is the constant of proportionality, $g_{ij} = 1$ if banks i and j are linked, otherwise $g_{ij} = 0$. These linkages can be represented succinctly in a matrix *G* known as the adjacency matrix. Each element of this matrix is g_{ij}, which is defined as above. One can then write equation (4) for each bank in the sample and write the system of equations in a matrix form as below:

$$\lambda \cdot V = G \cdot V \tag{5}$$

Each entry in vector V is $Centrality_i$. Examining equation (5), one can note that vector V is the eigenvector of matrix *G*. If *G* is not symmetric, the centralities are given by the right eigenvector of *G*. Equation (5) also has multiple solutions for eigenvectors, and, conventionally, one uses the eigenvector corresponding to the largest eigenvalue of matrix *G*. The Perron-Frobenius theorem guarantees that this eigenvector is non-negative, such that centrality scores for all banks are non-negative.[25]

The centrality score for each bank *i* as described in equation (4) weights each link only by the other banks' connectedness. The measure I construct also weights these linkages by bank *i*'s loan exposure to other banks. So, my definition for a bank's centrality accounts for (a) the subject bank's loan exposure to other banks, and (b) the centrality of other banks. This construction, therefore, allows my measure to capture contagion of distress occurring from other banks. Below, I describe how I construct this variable using a stylized network of four hypothetical banks (see Figure 1).

First off, I say that two banks are linked if they are exposed to a common housing market represented by an MSA (Metropolitan Statistical Area). Specifically, if two banks originate mortgage loans for properties located in the same MSA, I say that they are linked. For example, in Figure 1, bank A originates loans in MSAs *x*, *y*, and *z*, B

[25] See Meyer (2000).

originates loans in MSA *x*, C originates loans in MSAs *x* and *y*, while D originates loans in MSAs y and *z*. Therefore, in this example, A is linked with B, C, and D through MSAs x, y, and z. Similarly, C and D are linked through MSA y.

The numbers along the arrows represent portfolio weights that banks assign to each of the MSAs. For instance, A originates 30% of its loan portfolio in MSA *x*. This value represents bank A's loan exposure to other banks in MSA *x*. Note that the linkages here are directed. This is because (a) bank A's exposure to B, for example, is different from B's exposure to A, and (b) depending on how distressed A and B are, any contagion happening from A to B is going to be different from that happening from B to A. Weighting links by loan exposures this way captures a bank's vulnerability to contagion occurring from other banks.

I represent linkages in this hypothetical network in the adjacency matrix, *G*. Each element in this matrix is g_{ij}, which takes the value 1 if there is a link from bank *i* to *j* and 0 otherwise. I then construct a weighted version of matrix *G* using loan exposure amounts as weights, and label the matrix *W*. For instance, bank A's total loan exposures to banks B, C, and D are 0.3, 0.5, and 0.7 respectively, therefore the entries in matrix *W* reflect these numbers as weights.

Next, I compute the right eigenvector corresponding to the principal (largest) eigenvalue of matrix *W*. As discussed above, this eigenvector contains centrality scores for each of the banks in my sample. For example, the eigenvector corresponding to the principal eigenvalue of the adjacency matrix in figure 1 is (0.43 0.58 0.56 0.41). The entries in this vector are centrality scores for banks A, B, C, and D respectively. The bank with the highest score is bank B and the one with the lowest score is bank D. And bank B is 1.4 (=0.58/0.41) times more connected than bank D.[26]

To make these centralities comparable across time, I normalize them by dividing by the sum of centralities for all banks, and express them as percent values (see El-Khatib, Fogel, and Jandik (2015), Jackson (2008)). I compute these normalized centrality

[26] In this hypothetical example, although bank B is only connected to banks A and C, it has full loan exposure to those banks, such that the strength of its connectedness and thus its vulnerability to contagion from those banks and their linkages is stronger than any other bank.

scores for each bank during each of the years in the pre-crisis period (2005 and 2006). Then, I take the average of these numbers to obtain a measure of average connectedness during the pre-crisis period.

Because this centrality measure captures linkages that are not only one degree apart but also more than one degree apart, it captures greater complexity of a network. Therefore, it is more comprehensive in capturing exposure to other banks than a simple degree of links measure, which only counts the number of direct links.[27] For example, in figure 1, banks B and D are not connected, however B could still be vulnerable to the riskiness of D through bank A; distress at bank D could render bank A vulnerable, which in turn could affect bank B. Moreover, the centrality measure captures exposure to contagion better than measures that weight links by market share of other banks rather than their connectedness. This is because even a relatively small bank can have a more central position in a network and thus act as a conduit for transfer of distress from banks that are otherwise not linked with the subject bank.

b) Bank Stability

I use z-score as my primary proxy for stability, which is the dependent variable.[28] Z-score has been widely used in the banking literature as a measure of stability (e.g., Laeven and Levine (2009), Houston et al. (2010), Wang (2014)). It is defined as the sum of return on assets (ROA) and capital-asset ratio (CAR) divided by the standard deviation of ROA. It represents the number of standard deviations of a bank's ROA that has to drop before equity is depleted (or the bank is insolvent).[29] Intuitively, this measure represents

[27] Similar results obtain when I use degree of links weighted by subject bank's loan exposure to other banks as a measure of connectedness.

[28] I also use standard deviation of ROA as my measure of stability. Results are qualitatively similar when I use this variable. I present results only for the primary dependent variable, z-score, to save space.

[29] See Laeven and Levine (2009) for a description of the intuition behind this characterization of z-score.

distance to default; larger the value, the further away the bank is from insolvency and safer the bank. Specifically,

$$z - score_i = \frac{\frac{1}{T}\sum_{\tau=0}^{T} ROA_{i,\tau} + \frac{1}{T}\sum_{\tau=0}^{T} CAR_{i,\tau}}{\sigma_0^T(ROA_i)} \quad (6)$$

where *T* is the total number of quarters in the period being considered. ROA is defined as net income over gross total assets (GTA) and CAR is total equity capital over GTA for firm *i* in quarter *t*. In my regressions, I use the natural logarithm of z-score as a measure for financial stability. To ensure that I have sufficient number of observations to compute my dependent variable, I require that at least half of the bank's pre-crisis and half of the bank's crisis period observations are available (Berger and Bouwman (2008)).

In addition, when I use the probit model to study whether connectedness explains high declines in stability, I construct a dummy variable identifying declines in z-score (from pre-crisis to crisis) that is greater than the median for the sample. This translates to any change in z-score that is smaller than 9.6%.

c) Other Variables

In order to study mechanisms that affect the relationship between connectedness and stability, I construct dummy variables that identify whether the subject bank is linked with banks that have high leverage, are involved in greater degree of securitization activity, or have high liquid holdings ratio. I construct these variables as follows.

For leverage, I use Tier 1 risk-based capital ratio (Tier 1 capital/risk-based assets) available in call reports.[30] For a given bank, I first compute the average of this ratio for *other* banks in each of the MSAs where the subject bank originates loans. Then, I take the weighted average of these ratios, the weights being the portfolio weights that the subject bank assigns to each of the MSAs. (A portfolio weight is the fraction of loans that the

[30] The Federal Reserve uses this ratio to capture leverage of a bank. Capital requirements are also based on this ratio. In addition, I use Total Risk Based Capital Ratio (computed as the ratio of the sum of Tier1 and Tier 2 capital to risk-based assets), a second measure for capital ratio used by the Federal Reserve. Similar results obtain when I use this measure instead.

bank originates in an MSA.) If a bank has below median value for this variable, it means that the subject bank is linked with highly levered banks. I construct a dummy variable to indicate such banks and call it *Dummy High Other Leverage.*

I construct *Dummy High Other Securitization* and *Dummy High Other Liquidity* similarly. Securitization refers to the fraction of total loans that a bank sells in a given year and liquidity ratio is total liquid assets (cash plus fed funds sold plus securities excluding MBS and ABS securities; see Acharya and Mora (2015)) expressed as a fraction of GTA.

In addition, I include several control variables in my regressions. One of them is pre-crisis z-score, which is computed over the pre-crisis period. Since my sample consists of bank holding companies as well as stand-alone banks, I also include an indicator variable identifying a bank holding company to account for any differences between the two. Furthermore, I include the natural logarithm of total deposits (deflated to 2009 dollars) as a proxy for bank size, asset quality (ratio of non-performing loans to total loans), and management quality (overhead costs/GTA).

Next, I control for the exposure of a bank to market concentration of the MSAs where it originates loans. To construct this variable, I first compute Herfindahl-Hirschman Index (HHI) for each MSA. HHI is measured as the sum of squares of market shares of all lenders in a given MSA in a given year. This value ranges from zero to one – zero indicating the least concentration of lenders, and one indicating the highest degree of concentration. I then compute the concentration exposure of a bank by taking a weighted average of HHI for all MSAs where the bank originates loans, and, as before, the weights reflect the fraction of loans that the bank assigns to each MSA.

I also include a control variable for local economic conditions that can potentially affect the stability of a bank. I obtain unemployment rates for each MSA from the Bureau of Labor Statistics, and compute a given bank's exposure to local economic conditions by computing weighted average unemployment rates in the MSAs where the bank originates loans. Again, the weights reflect portfolio fractions that the bank assigns to each MSA. Similarly, I control for housing market conditions by including weighted average home price changes (from the previous year to current year) in the MSAs where the bank originates loans. I use house price index (HPI) (traditional, all-transactions index) provided by FHFA to compute such home price changes.[31]

To ensure that my results are not influenced by outliers, I winsorize all variables at 1%. Summary statistics appear in Table 1.1. Panel A presents summary statistics for all variables used in the regressions, while Panel B compares key variables for large and small banks. Comparison of z-score levels during crisis and pre-crisis periods indicate that large banks are, on average, riskier than small banks. Moreover, z-score falls during the crisis period for both size groups as expected. Also, large banks are, on average, more levered than small banks, and large banks are more involved in securitization activity than small banks. While large banks sell on average 34% of their mortgage loans, small banks sell 21% of their loans. Similarly, small banks hold greater amounts of liquid assets as a fraction of total assets than do large banks (26% for small banks versus 18% for large banks).

1.6 Main Results

1.6.1 Univariate Results

As a preliminary analysis, I begin with a visual investigation of the relationship between interconnections and stability of a bank during pre-crisis and crisis periods. Figure 2, panel A(i) presents a plot for the pre-crisis period. It plots average z-score levels (measured over 2005-2006) for banks having eigenvector centrality (measured

[31] I obtain HPI Index data from FHFA at https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx#atvol. Since FHFA uses February 2013 definitions for MSAs, I use the 2009 to 2013 crosswalk table from the same website and various historical delineation files from the census website to obtain 2013 MSAs corresponding to the MSAs in my sample. For older MSAs prior to and including 2005 in my sample, I use the crosswalk file available from http://www.nber.org/data/cbsa-msa-fips-ssa-county-crosswalk.html.

over 2003-2004) in the four quartiles of the distribution for the sample. I contrast this graph against a plot for the crisis period (panel A(ii)) in which z-scores are measured over the crisis period of 2007-2009 and centrality is measured over the pre-crisis period of 2005-2006.

While Panel A(ii) suggests that z-score of a bank during crisis declines as connectedness increases, the plot for the pre-crisis period, presented in panel A, displays no clear relationship between the two. This suggests that the negative relationship between connectedness and stability is likely being triggered by the shock of the housing crash.

Panel B contrasts the crisis period plot (Panel A(ii)) for banks whose linkages are stable (banks having high other z-score), with those whose linkages are risky (banks having low other z-score).[32] The figure shows that banks linked with stable banks themselves have high z-score on average. The figure also suggests that stability declines at a faster pace with increasing centrality for banks that are connected to riskier banks. This is suggestive of spillover effects occurring from risky banks. Regression results in the next subsections support this idea.

Figure 3 extends these plots by contrasting the crisis period plot in Panel A(ii) for small banks against that for large banks, and by considering different mechanisms that affect the relationship between interconnections and stability. Panel A presents average crisis z-scores (measured over 2007-2009) for small versus large banks having centrality in different quartiles (measured over 2005-2006). The figure shows that as connectedness increases, z-score levels decline for both sizes. While small banks have higher stability on average, stability declines at a faster rate for them compared to large banks.

Panel B contrasts plots for banks linked with highly levered banks (i.e., banks having leverage greater than the median for the sample) with those that are linked with banks having low leverage (i.e., banks having leverage below the median for the sample). Small banks that are linked with highly levered banks are, on average, risker and z-score

[32] Banks having high other z-score are banks that have above median value for weighted average z-score of *other* banks that are linked with the subject bank. As before, weights reflect the portfolio weights that the subject bank assigns to each of the MSAs where it originates loans.

declines with increasing connectedness at a greater rate. For large banks, the differences in banks linked with high versus low leverage banks are not clear. However, multivariate results will show later that leverage of other banks is a contagion-magnifying mechanism for both small and large banks alike.

Similarly, panel C contrasts plots for banks whose linkages are involved in high degree of securitization activity with plots for banks whose linkages are involved in low degree of securitization activity. For large banks, there is a declining relationship between centrality and z-scores if other banks are involved in high degree of securitization, while it is unclear how they are related if other banks are not involved in as much securitization. This suggests that securitization activities of other banks potentially amplify the contagion effect of connectedness for large banks. Small banks are, on average, risker if other banks are involved in high degree of securitization than if they were involved in low degree of securitization. However, the rate at which stability declines with increasing connectedness is lower if others did more securitization. One possible reason for why small banks do not show much sensitivity to securitization as a contagion-magnifying mechanism is because these banks are not as involved in securitization as large banks are (Table 1.1, panel B).

Finally, panel D explores the effect of liquid holdings of other banks. Banks whose linkages hold high amounts of liquid assets are more stable than those whose linkages hold low amounts of liquid assets. Furthermore, the declining relationship between centrality and z-score is steeper if other banks hold smaller amounts of liquid assets, and this effect is observable in both large and small banks.

1.6.2 Interconnections and Stability

Table 1.2 studies whether a bank's eigenvector centrality impacts its stability. According to Hypothesis 1, when there is a large enough negative shock, interconnections serve as channels of contagion and thus hurt the stability of the financial system.

The model in columns (1)-(3) regresses crisis z-score on pre-crisis eigenvector centrality and other control variables. Column (1) presents results for the whole sample, while columns (2) and (3) present results for large and small bank subsamples respectively. Results indicate that centrality of a bank is negatively related to its stability during crisis. This result is driven by small banks despite the fact that they are relatively more stable than large banks during the pre-crisis period (see Table 1.1, panel B). Although centrality is statistically insignificant for large banks, further results will show that there are mechanisms that amplify contagion effect and even large banks are vulnerable to this effect.

These results are economically significant as well. For example, consider the coefficient on *Eigenvector Centrality* in the first column for the whole sample. This coefficient says that an increase in centrality of a bank from 25^{th} to 50^{th} percentile decreases the stability of an average bank by 2.8%. For a small bank, stability declines by 5.1%.

Other control variables show intuitive relationships with stability. Results for the full sample show that banks that are more stable during the pre-crisis period have greater stability during crisis as well. If the pre-crisis z-score is a percentage point higher, there is approximately half a percentage point increase in z-score during crisis. Exposure to high unemployment rates and high increases in home prices decreases the stability of the bank during crisis. Similarly, lower asset quality results in lower stability, and a bank holding company is riskier than an independent bank.

Columns (4)-(5) present results for the probit model which tests whether connectedness of a bank during pre-crisis predicts a high decline in stability during crisis. The marginal effects indicate that an increase in the centrality of an average bank from 25^{th} to 50^{th} percentile results in a 1.5% increase in the probability of a high decline in z-score. Again, this result is mainly driven by small banks.

Overall, the results in table 1.2 suggest that during the crisis period, having high connectedness makes a bank riskier, potentially amplifying the effects of the initial shock.

1.6.3 Contagion

The previous section showed a negative relationship between connectedness and stability. In this section, I show that this result is due to contagion of risk from other banks. It will also follow that this result is not due to competition effect, which could also lead to higher risk by decreasing margins for the subject bank.

To that end, I ask whether being connected to other risky banks implies that the subject bank is also risky. This would be true if there was contagion of risk occurring from other banks. On the other hand, if competition were true, being connected to riskier banks should imply that the subject bank is able to perform better and thus is more stable. One could also argue that a bank could compete with other risky banks by increasing its own riskiness. However, this scenario is unlikely for the setting of this paper. I study riskiness of a bank during crisis, which was a period of great recession, and it is unlikely that banks were expanding their assets during this time. Literature provides ample evidence on how banks reduced lending during crisis (see Ivashina and Scharfstein (2010), Cornett et al. (2011)). In fact, Dagher and Kazimov (2015) use the same database that I use to show that banks contracted lending during crisis.

I begin by constructing a variable that captures a bank's exposure to stability of other banks. This is the weighted average z-score of all other banks that are linked with the subject bank. The weights reflect the subject bank's loan exposures to other banks. I then construct a dummy variable that identifies whether the average z-score of other banks is above the median for the sample.

Table 1.3, panel A presents estimates for the specification in equation (3) in which I interact eigenvector centrality with the dummy variable just described. Columns (1)-(3) perform OLS regressions using *log(crisis z-score)* as the dependent variable, for the whole sample, the large bank subsample, and the small bank subsample respectively. Columns (4)-(6) present results for the probit model. The interaction terms are statistically significant in all columns and they indicate that being connected to riskier banks during pre-crisis means that the subject bank is riskier during crisis.

These results are also economically significant. Specifically, for an average bank (see column (1)) which is connected to banks having high z-score (less risky exposure), an increase in centrality from 25th to 50th percentile decreases stability by only 2.4%, while the stability of a bank connected to banks with low z-score (more risky exposure) decreases by 29.5%. The probit model implies that a similar increase in centrality increases the probability of a high decline in z-score for a bank with high risk exposure by 10.7%, but for a bank with low such exposure, the probability only increases by 1.2%. Similar results hold for large and small bank subsamples.

In panel B, I find that these results hold whether the subject bank is ex-ante risky or stable. Specifically, I rerun the previous test in two subsamples – one containing banks having high own pre-crisis z-score (own pre-crisis z-score is greater than the median for the sample) and the other containing banks having low own pre-crisis z-score. Results show that both of these categories are susceptible to contagion. For a bank that is ex-ante stable but connected to risky banks, an increase in centrality from 25th to 50th percentile decreases its stability by 21.7%. Similarly, for a bank that is ex-ante risky and connected risky banks, a similar increase in centrality decreases stability by 32.9%. The persistence of the result after stratifying the main sample by own pre-crisis z-score decreases concerns of other factors like common market conditions driving the results.[33] Moreover, banks that are ex-ante risky are more sensitive to the stability of other banks as one would expect if there is any contagion happening from other banks.

In panel C, I consider linkages to risky banks and stable banks separately. Here, I define stable banks as those that have ex-ante z-score in the top quartile of the distribution of the sample, and risky banks as those that have ex-ante z-score in the bottom quartile.[34, 35] Columns (1) and (2) show that when I consider linkages only to risky banks, there is a statistically significant and negative relationship between a bank's

[33] Section VII conducts several other robustness tests to address potential effect of such common conditions on the results of this paper.
[34] Similar results obtain when I define banks having above median z-score to be stable and below median z-score to be risky.
[35] Considering linkages only to risky banks implies that I assume that the subject bank is not connected with other banks that are not risky, even if those banks overlap with the subject bank in an MSA.

connectedness and its stability. An increase in centrality of a bank from 25th to 50th percentile decreases the stability of a bank by 1.7%. However, when I consider linkages only to stable banks (columns (3) and (4)), centrality of a bank loses its statistical significance. This result provides evidence that the centrality score variable is capturing spillover effects from other risky banks.[36]

1.6.4 Contagion Amplifying/Mitigating Mechanisms

a) Leverage of other banks

Table 1.4 explores leverage of other banks as a potential mechanism that amplifies the contagion effect of interconnections. According to hypothesis 2, the negative relationship between connectedness and stability of a bank should be more pronounced for banks that are connected to highly levered banks.

Columns (1) through (3) present results for the OLS model. Consistent with hypothesis 2, they suggest that exposure to banks having high leverage amplifies the negative relationship between connectedness and stability for both large and small banks. This result is economically significant. For an average bank that is connected to banks having low leverage, column (1) in table 1.4 (whole sample results) suggests that an increase in centrality from 25th to 50th percentile implies a 2.1% decline in z-score. On the other hand, a similar increase in centrality of an average bank linked to highly levered banks implies a 23.1% decline in z-score.

Columns (4) through (6) present estimates for the probit model. Similar results obtain. As per column (4), if centrality increases from 25th to 50th percentile, the probability of a high decline in z-score for an average bank with low other leverage increases by 0.8%, while that for a bank with high other leverage increases by 11.1%.

[36] When I consider linkages only to stable banks, there are two banks that do not have any linkage to stable banks. I drop observations for these two banks. This explains the smaller sample size in columns (3) and (4).

Overall, results in table 1.4 show that leverage of other banks is an important mechanism that amplifies the contagion effect of interconnections.

b) Securitization activity of other banks

Table 1.5 considers securitization activity of other banks as another mechanism that amplifies the magnitude of contagion through linkages. According to hypothesis 3, the negative impact of interconnections on a bank's stability during crisis should be more pronounced for banks that are exposed to higher levels of securitization activities of other banks.

Results in table 1.5 show that securitization activity of other banks is indeed a contagion-amplifying mechanism, especially for large banks. While the OLS model suggests that small banks are also vulnerable to this channel, the result is not robust to probit specification. Panel B of Table 1.1 reveals that large banks were, on average, more involved in securitization activity than small banks during the pre-crisis period. They sold 34% of their loans during the pre-crisis period, while small banks sold 21% of their loans. This difference is statistically significant as well. Therefore, it is sensible that large banks show greater sensitivity to this channel than small banks. For example, when the secondary market freezes, large banks are likely forced to hold greater fraction of their loans that they intended to sell. To the extent that loans meant for sale are of poorer quality, these banks should be affected more when the secondary market freezes.

These results are also economically significant. According to the OLS model in column (2), for a large bank with high other securitization, an increase in centrality from 25^{th} to 50^{th} percentile decreases z-score by 18.3%. On the other hand, centrality is not statistically significant for large banks having low other securitization. Similarly, the probit model results in column (5) suggest that a similar increase in centrality results in a 9.8% increase in the probability of a high decline in z-score for a large bank with high other securitization. Again, results are statistically insignificant for a large bank with low other securitization.

Overall, results in table 1.5 suggest that the degree of securitization activity of other banks is an important mechanism that amplifies contagion through linkages.

c) Liquid holdings of other banks

Finally, table 1.6 considers contagion-mitigating effect of liquid holdings of other banks. According to hypothesis 4, the magnitude of the negative relationship between connectedness and stability should be smaller for banks that are connected to banks holding higher levels of liquid assets than for those that are connected to banks holding lower levels of liquid assets.

Results in table 1.6 are consistent with this hypothesis – the effect of this mechanism is statistically and economically significant for both large and small banks. According to the OLS model in column (1), an increase in centrality from 25^{th} to 50^{th} percentile implies a 25.9% decrease in z-score for an average bank with low other liquidity. On the other hand, a bank with high other liquidity faces only a 2.3% decline in z-score.

Similarly, probit model results suggest that if other banks hold greater amounts of liquid assets, the probability of a high decline in z-score decreases for the subject bank. For example, for an average bank (column (4)) with low other liquidity, an increase in centrality from 25^{th} to 50^{th} percentile implies a 10.4% increase in the probability of a high decline in z-score, while for a bank with high other liquidity, it implies a decrease of 0.8% only.

Overall, results in table 1.6 show that increased liquid holdings of banks help mitigate the contagion effect of interconnections.

1.6.5 Placebo Tests

a) Placebo Event

Here, I investigate whether my results are robust to a placebo event. For this, I rerun all of my tests using a false crisis period of 2005-2006. I use 2003-2004 as the corresponding pre-crisis period. If the shock of the 2007 housing crash was triggering contagion and thus the negative relationship between centrality and stability, then those results should not show in this placebo test.

Table 1.7 presents the results. Columns (1) through (5) present OLS estimates for the model that studies the relationship between centrality and stability, and for the ones that study the effect of stability, leverage, securitization, and liquidity ratio of other banks on subject bank's stability. Rest of the columns presents results for the probit model. To preserve space, I only tabulate results for the full sample. None of the results are statistically significant, thus providing evidence that the results documented earlier are attributable to the 2007 housing crash. [37]

b) Placebo Linkages

Next, I conduct a test using placebo linkages. Specifically, in a given MSA, I identify banks that sell all of the loans that they originate by the end of the year, and obtain a subsample of those loans that are sold. Any interbank linkage that these loans represent are broken and thus non-existent. If my prior results are being driven by the specific linkages that I define, then there should be no reason why similar results should obtain for a test that uses these placebo linkages.

Table 1.8 presents the results. Again, I present results for the full sample only. Columns (1) through (4) present OLS estimates, while columns (5) though (8) present

[37] I obtain similar results for large and small bank subsamples; none of the results are statistically significant.

estimates for the probit model. These include the base model that studies the relationship between centrality and stability, and the models that study the impact of stability, leverage, and liquid holdings of other banks on this relationship.[38] Again, none of the results are statistically significant. Thus, these results provide evidence that the mechanism behind the construction of linkage drives my results.

1.7 Robustness Tests

This section conducts additional tests to check the robustness of my main results.

1.7.1 Exposure to common market conditions

Here, I address the possibility that my measure for connectedness might capture the effect of housing market conditions rather than contagion occurring from other banks. To this end, I compare results for banks having different levels of exposure to housing bubble markets. Since bubble markets likely suffered the most when the housing shock hit, if the results of negative relationship between interconnections and stability are being driven by common market conditions, they should be strongest for banks that have the highest exposure to these bubble markets, and they should be weakest for those that have the least exposure.

A commonly used measure to identify housing bubble markets is the ratio of median home price to median household income (Mccarthy and Peach (2004)). High home prices relative to income are indicative of investors over-pricing home values. The U.S census bureau's American Community Survey provides data on median home price and median household income. I obtain these data for 2005 and 2006, and for each year, I define MSAs having this ratio in the top quartile range as bubble markets. Then, I

[38] This test does not study securitization activity of other banks as a contagion-amplifying mechanism because the sample only includes banks that sell all of the loans that they originate in a given MSA.

compute each bank's yearly exposure to these markets using the fraction of home loans that they originate in these MSAs, and take the average of these exposures in 2005 and 2006. Finally, I construct dummy variables that identify banks having bubble market exposure in different quartiles, and study how these variables interact with the centrality measure. This lets me study how the relationship between connectedness and stability varies with varying exposure to bubble markets.

Column (1) of table 1.9 presents results for the model that includes interaction of centrality with all dummy variables that identify different quartiles of exposure to bubble markets, and quartile 1 serves as the base group. If market conditions were driving the results, I would expect the interaction terms to be negative and significant, and increasing in magnitude with increasing quartile level (i.e., with increasing bubble market exposure). However, results show that the negative relationship between centrality and stability for banks in the 2nd quartile is not statistically different from that for the banks in the 1st quartile, which have the least exposure to bubble markets. While the results for the 3rd and the 4th quartile banks are statistically different from those for the 1st quartile banks, the interaction term is positive and increasing, implying a decrease in the magnitude of the negative relationship between connectedness and stability with increasing exposure to bubble markets. Moreover, the coefficient for the 4th quartile banks – the banks that have the highest exposure to bubble markets – more than offsets the negative coefficient of centrality for the 1st quartile banks. This suggests that it is unlikely that market conditions are driving the negative relationship between interconnections and stability.

I conduct further tests using a subsample of banks that have no exposure to bubble markets in column (2) and a subsample of banks that have full exposure to bubble markets in column (3). Again, if market conditions were driving my results rather than contagion arising from other banks, results should be strongest in banks having full exposure to bubble markets, and they should be weakest in banks having no such exposure. On the contrary, I find that the coefficient for centrality is negative and significant for the no exposure subsample, while it is statistically insignificant for the full exposure subsample.

Since the full exposure subsample is rather small, to address concerns that the sample size may have reduced the power of the test in column (3), the 4th column considers a random subsample of similar size from the no exposure sample. Again, the coefficient for centrality in this random subsample is negative and statistically significant.

Columns (5) through (8) perform similar tests using the probit model, and results are robust to this specification as well. Overall, these results imply that the negative relationship between interconnections and stability is not merely being driven by common market conditions.

1.7.2 Placebo linkages and exposure to market conditions

In this subsection, I provide additional evidence that my results are not merely being driven by common market conditions. Here, I consider placebo linkages that still capture valid exposure to housing market conditions. Specifically, in a given year and MSA, I first identify banks that hold on to some of the loans that they originate (i.e., banks that engage in portfolio lending) and banks that sell all of the loans that they originate by year end. Then I consider linkages from portfolio lenders to those lenders that sell all of their loans in the given market. Therefore, these linkages are broken and non-existent, but they still capture the subject bank's exposure to market conditions. Additionally, I make sure that these banks engaged in portfolio lending are not connected to banks that sell all of their loans though other markets.

If prior results on contagion effect are in fact due to contagion, then these results should not appear in this test since the linkages are broken. However, if market conditions are driving the results, I expect similar results to hold because these linkages still capture the subject bank's exposure to market conditions.

Table 1.10 presents the results. Results for the OLS model are presented in columns (1) through (4), while those for the probit model are presented in columns (5) through (8). Although the variable centrality is statistically significant in the base models that study the relationship between centrality and stability in columns (1) and (5), none of the prior results pertaining to contagion effect are observable anymore. The OLS model in column (2) suggests that high stability of other banks decreases the stability of the subject bank – a result opposite to previous ones – although this result is not robust to probit specification. So, there is no evidence that being connected to riskier banks makes the subject bank riskier. Similarly, there is no evidence that being connected to banks with high leverage or low liquid holdings makes the subject bank riskier.[39]

Overall, the results of this test using placebo linkages that still capture the subject bank's exposure to market conditions provide additional evidence that the results of this paper are not merely being driven my market conditions and that they are indeed capturing contagion effect.

1.7.3 Exclusion of the top 1 percentile bubble markets

This subsection conducts yet another test to address concerns that common market conditions might be driving my results. Here, I show that removing banks that originate loans in the top 1 percentile housing bubble markets does not change my results. If it did, it would indicate that common conditions of the worst markets are driving my results. I first identify MSAs that have price-to-income ratio greater than or equal to the top 1 percentile level for the sample, and obtain a subsample of lenders that do not originate mortgages in these MSAs during the pre-crisis period. This subsample consists of 1291 lenders. Table 1.11 presents results for this sample. All prior results on the relationship between connectedness and stability, as well as results pertaining to mechanisms affecting this relationship persist.

[39] Again, this test does not study securitization activity of other banks as a contagion-amplifying mechanism, because the "other" banks in the sample are banks that sell all of the loans that they originate in a given MSA.

1.7.4 Public bank subsample

In this section, I test whether my results are robust to using alternate measures of dependent variable that are based on stock return data. To that end, I perform my analysis in a subsample of public banks. I use an overall market risk measure and a measure of idiosyncratic risk, which I will describe shortly. While limiting my sample to public subsample reduces sample size, this test shows that my results are robust to alternate measures. Moreover, the study of the idiosyncratic risk serves as another test to alleviate concerns that the implications of connectedness on bank risk could be driven by overall systematic risk.

First, using the CRSP-FRB Link provided by the Federal Reserve Bank of New York, I identify public banks and link them to CRSP (Center for Research In Security Prices) to obtain stock price data. I compute overall market risk for each bank by taking the standard deviation of weekly market returns during the crisis period. Similar to Goetz, Laeven, and Levine (2016) and Gatev, Schuermann, and Strahan (2009), I obtain weekly returns observed on Wednesdays since this day of the week has the fewest holidays.

I then construct my second measure for riskiness – the idiosyncratic risk. Following Goetz, Laeven, and Levine (2016) and Gatev, Schuermann, and Strahan (2009) again, I remove systematic risk factors, and compute the standard deviation of the idiosyncratic portion of a bank's return. Specifically, I run the following regression:

$$r_{i,t} = \alpha_i + \beta_{1,i}\, r_{m,t} + \beta_{2,i}\, \Delta(Baa - Aaa)_t + \beta_{3,i}\, \Delta(3 - month\ T - bill)_t + \epsilon_{i,t} \qquad (7)$$

where $r_{m,t}$ is weekly return of the S&P 500 index, $(Baa - Aaa)_t$ is default risk factor computed as the change in difference between yields on *Baa* and *Aaa* rated corporate bonds, and $(3 - month\ T - bill)_t$ is interest risk factor computed as the change in the yield of a 3-month treasury bill. I obtain data for these variables from the Federal Reserve Economic Data provided by the Federal Reserve Bank of St. Louis. Then, I run the regression in (7) for each bank *i* separately, and collect residuals from each of these regressions. The standard deviation of these residuals represents the idiosyncratic risk of a bank.

Table 1.12 presents the results. Columns (1) and (6) corroborate prior results that connectedness increases riskiness of a bank. Specifically, the centrality of a bank increases the overall equity return risk of the bank, and focusing on the idiosyncratic part of the market risk does not change this result. Columns (2) and (7) show that being connected to risky banks increases the riskiness of the subject bank, and columns (3) and (8) show that leverage of other banks amplifies the negative relationship between connectedness and stability. However, there is no statistically significant evidence that securitization activity of other banks is a contagion-amplifying mechanism. One possible reason for this result is that the majority of banks in this sample is large and, therefore, most are involved in greater degree of securitization activity, such that there is not much variation in the degree of their involvement in securitization. Moreover, the size of this subsample is smaller than the main sample. Given the amount of evidence so far on the effects of securitization, its potential negative impact cannot be ignored. Finally, Columns (5) and (10) show that high liquid holdings of other banks mitigate the negative effect of connectedness on both overall market and idiosyncratic risk.

1.7.5 Linkages less likely to be broken

As described in the beginning of this paper, linkages that I construct are based on loans that are not sold as of the calendar year end. Although banks hold these loans in their portfolio, it is possible that they may decide to sell some of these loans after the calendar year end. This is true especially for loans that banks originate towards the end of the year and sell them during the beginning of the following year. The HMDA database does not provide information on whether loans are sold in following years. While results on placebo linkages based on sold loans (in section VI.5.B) show that broken linkages do not affect my results, I conduct another test here to address concerns that my results could be affected by linkages that break.

For this test, I construct linkages using loans that are less likely to be sold – jumbo loans and subprime loans. I define loans as jumbo if they are greater than $417,000 in size. These loans are less likely to be sold because Fannie Mae and Freddie Mac, who are the primary buyers of mortgages, do not buy loans above this cutoff. Moreover, it was difficult to sell loans in the non-agency market during crisis. Similarly, the Freddie Mac announced during the beginning of the crisis that it would not buy subprime loans. Since HMDA does not provide information on whether loans are prime or subprime, I follow Dell'Ariccia, Igan, and Laeven (2012) and use the list of subprime lenders provided by the Department of Housing and Urban Development (HUD), flagging loans from these lenders as subprime.[40]

Table 1.13 presents results for the full sample. While the base model that regresses stability on centrality (columns (1) and (5)) does not show a statistically significant relationship between the two, I find that all of the other results pertaining to contagion, i.e., the effect of stability, leverage and liquid holdings of other banks on the subject bank's stability persist in this subsample. Moreover, the economic magnitude of the results is comparable to prior results.[41]

1.8 Policy Implications

This section derives policy implications for minimum levels of capital and liquidity ratios that could potentially contain spread of risk. The events of the crisis revealed that the capital requirements in place at the time were not enough, and, since then, Basel III has been introduced, which has increased the requirement on Tier 1 capital ratio and has also introduced new liquidity requirements, one of which requires banks to hold enough liquid assets to withstand a stress scenario. This section asks whether certain

[40] This list is available at https://www.huduser.gov/portal/datasets/manu.html.

[41] This table does not study securitization activity of other banks as a contagion-amplifying mechanism because the linkages considered here are based on loans that are less likely to be sold, such that the banks in the sample are biased towards those that are less involved in securitization.

levels of capital and liquid holdings ratios could have helped contain spillover effects during crisis.

In order to answer this question, I study the distribution of capital and liquidity ratios of other banks, and study their impact on the relationship between interconnections and stability for the subject bank. Specifically, I estimate model (3), but now I interact centrality with dummy variables that identify exposure to capital and liquid holdings ratios of *other* banks at different quintiles. Since the Federal Reserve imposes requirements on two types of capital ratios – Tier 1 risked based capital ratio and Total risk based capital ratio – I present results for both of these ratios. These ratios are reported by banks in call reports.

The cutoff points for different quintiles of the distribution of Tier 1 capital ratio of *other* banks are 0.106, 0.110, 0.116, and 0.125; the cutoff points for Total capital ratio of *other* banks are 0.129, 0.132, 0.137, and 0.144; and the cutoff points for liquid holdings ratio of *other* banks are 0.139, 0.150, 0.163, and 0.184. Panel A of table 1.14 presents results.

The first column includes dummy variables identifying different quintiles of a bank's exposure to Tier 1 capital ratio of other banks. The first quintile acts as the base group, which shows a significantly negative relationship between connectedness and stability. While banks in the 2^{nd} and 3^{rd} quintile are not statistically different from the base group, the ones in the 4^{th} and 5^{th} quintile are. The positive interaction terms indicate declining negative impact of connectedness on stability with increasing capital ratio of other banks. I find that for the 5^{th} quintile banks, the impact of centrality on stability is not statistically significant.[42] This suggests that banks having Tier 1 capital ratio >12.5% did not contribute in contagion of distress. This result could inform policymakers in designing minimum capital requirements.

Although 12.5% is higher than the capital requirement in place at the time of this writing, in light of the recent literature that suggests that the costs of increasing capital requirements are not too high for banks (Kisin and Manela (2016), Baker and Wurgler

[42] The sum of *Eigenvector Centrality (EC)* and *EC * Other Tier1 Risk Based Capital Ratio in 5^{th} quintile* is not statistically significant.

(2015)), the benefits of higher capital requirements could be greater given their role in maintaining the financial health of the banking system by reducing spillover effects.[43,44,45] Also note that because I consider only one type of linkage in this paper, the estimates of the magnitude of the relationship between interconnections and stability that I report are underestimates, so the capital ratios suggested here are minimum levels that would be necessary to contain spillover effects.[46]

The second column in table 1.14 considers the distribution of Total capital ratio of other banks and explores its impact on the stability of the subject bank. The effect of centrality on stability is statistically insignificant for the 5th quintile group in this test as well, suggesting that banks having total capital ratio greater than 14.5% did not contribute in spreading risk. Finally, the third column shows that the subject bank is safer as other banks hold more liquid assets. Centrality is statistically insignificant for banks that are linked to banks having liquid holdings in the 5th quintile. This suggests that banks with liquid holdings ratio greater than 18.4% did not contribute in spreading risk.

Panel B of table 1.14 studies whether holding high capital and liquid assets helps the subject bank protect itself from contagion of risk occurring from other banks. The variable *High Tier 1 Capital Ratio* indicates whether the subject bank's own Tier 1 capital ratio is greater than the median for the sample. *High Total Capital Ratio* and *High Liquidity Ratio* are defined similarly. Results show that banks that hold high amounts of capital and liquid assets are still vulnerable to contagion arising from other banks; the

[43] Tier 1 capital requirement at the time of this writing was 8.5% (minimum capital ratio of 6% plus capital conservation ratio of 2.5%). Additionally, advanced approaches banks are subject to a countercyclical capital buffer requirement ranging between 0 - 2.5% at the regulator's discretion. At the time of this writing, this buffer was set at 0%.

[44] Kisin and Manela (2016) estimate that 1% increase in capital requirements would cost 0.4% of annual profits, 0.3 basis points increase in lending rates, and 0.15% decrease in lending amount. Similarly, Baker and Wurgler (2015) estimate that a 10% increase in Tier 1 capital ratio would increase weighted average cost of capital by 60 to 90 basis points per year.

[45] This result is also in line with a call for higher capital requirements by a group of financial economists in a letter to the Financial Times (see https://www.ft.com/content/63fa6b9e-eb8e-11df-bbb5-00144feab49a).

[46] I use capital ratios reported by banks during the pre-crisis period for my analysis here. The definitions for capital ratios have changed since the financial crisis (allowable capital and risk categories for determining risk weights for assets have been revised). So, the implications for the capital ratios per new definitions could be different.

magnitude of the relationship between centrality and stability for these banks is not statistically different from that for the banks that hold low amounts of capital and liquid holdings. This result highlights the role for policymakers in imposing appropriate capital and liquidity requirements to ensure the stability of the banking system.

1.9 Conclusion

This paper studies the impact of a bank's connectedness on its financial stability. I consider linkages that are formed between banks when they are exposed to common housing markets and show that these linkages facilitate contagion of risk initiated by the shock of the 2007 housing crash. While small banks are, in particular, more vulnerable to spillover effects, further tests show that there are mechanisms that amplify the contagion effect of linkages and even large banks are susceptible to these vulnerabilities.

I find that leverage and securitization activity of other banks amplify the magnitude of contagion, while liquid holdings of other banks mitigate this effect. Furthermore, I find that banks that have Tier 1 capital ratio greater than 12.5% and banks that have liquidity ratio greater than 18.4% did not contribute in contagion of risk. These results suggest minimum levels of capital and liquidity ratios that could contain spillover effects.

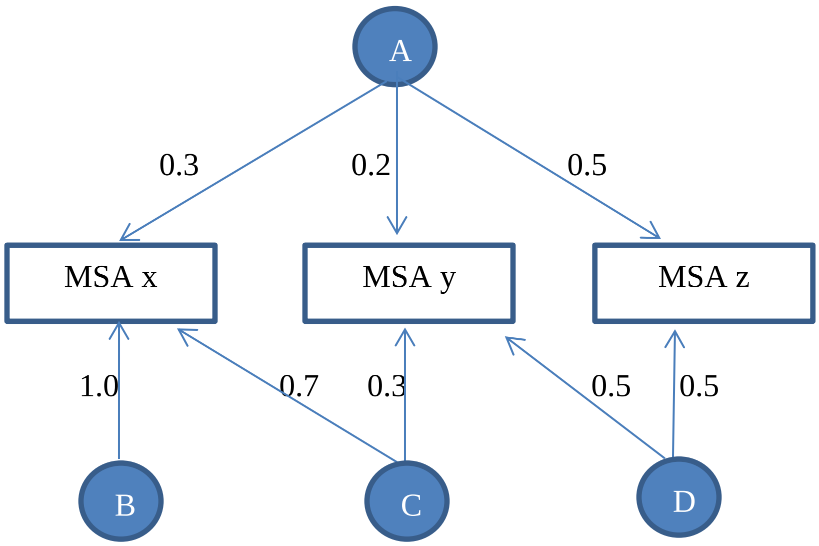
This paper makes a contribution to the literature by identifying a novel linkage that exists between banks and by showing that this linkage facilitates contagion of risk from one bank to another. Such empirical link between interbank connections and stability is missing in the literature (Glasserman and Young (2016)). Moreover, identifying mechanisms that magnify or mitigate the extent of contagion is another contribution of this paper.

The results of this paper are important to policymakers, who seek to understand mechanisms that facilitate contagion and seek ways to prevent contagion to ensure the stability of the banking system. Furthermore, with the introduction of new capital and liquidity requirements, there is an increased interest in understanding whether these requirements are adequate. By suggesting minimum levels of capital and liquidity ratios that could contain contagion, I also contribute to the discussion on the adequacy of these new requirements.

Further research is needed to understand other ways that banks can be linked with one another, such as the way banks can be linked due to common asset holdings or due to common regulation. Study of spillovers through those linkages would broaden our understanding of how connectedness impacts stability, and help policymakers design more precise policies to ensure a robust financial system.

Figure 1-1. Network Centrality

This figure displays a stylized network of four hypothetical banks A, B, C, and D that originate loans in MSAs (Metropolitan Statistical Area) x, y, and z. It illustrates the construction of adjacency matrix needed for computing eigenvector centralities of the banks in the network. Each arrow indicates that the bank originates loans in the given MSA. The numbers against the arrows are portfolio weights that banks assign to each MSA. These portfolio weights thus represent loan exposures of a bank to another. Matrix G is the adjacency matrix, which provides an unweighted representation of bank linkages. Each entry in G, gij, takes the value 1 if i has loan exposure to j, otherwise is takes the value 0. Matrix W is the weighted adjacency matrix, which weights each linkage by loan exposure.



$$\text{Adjacency matrix } G: \begin{array}{c} \\ A \\ B \\ C \\ D \end{array} \begin{array}{c} \begin{array}{cccc} A & B & C & D \end{array} \\ \begin{bmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & 1 & 0 \\ 1 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \end{bmatrix} \end{array}$$

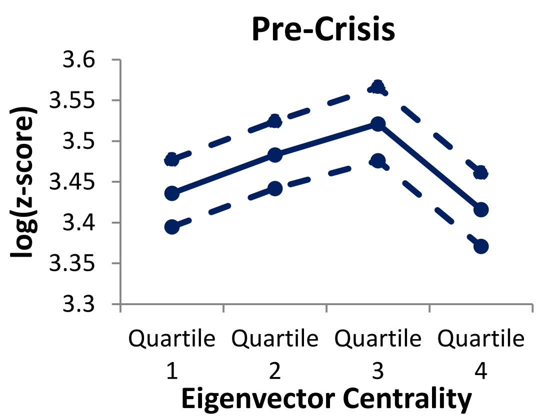
$$\text{Weighted adjacency matrix } W: \begin{array}{c} \\ A \\ B \\ C \\ D \end{array} \begin{array}{c} \begin{array}{cccc} A & B & C & D \end{array} \\ \begin{bmatrix} 0 & 0.3 & 0.5 & 0.7 \\ 1 & 0 & 1 & 0 \\ 1 & 0.7 & 0 & 0.3 \\ 1 & 0 & 0.5 & 0 \end{bmatrix} \end{array}$$

Figure 1-2. Connectedness and Stability

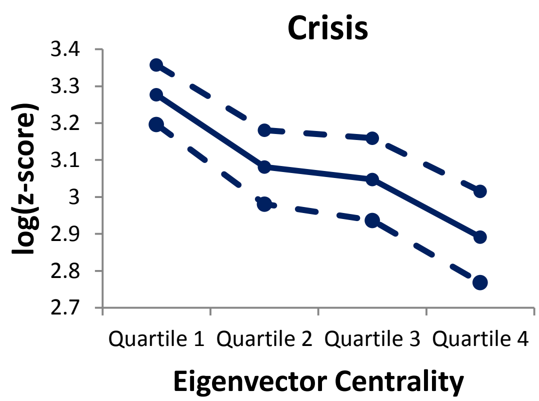
This figure plots the relationship between stability and connectedness prior to and during the crisis period. Panel A plots mean z-scores (logged values) for banks having *Eigenvector Centrality* in different quartiles. In Panel A(i), z-scores are computed over 2005-2006 and centrality scores are computed over 2003-2004. In Panel A(ii), z-scores are computed over 2007-2009 and centrality scores are computed over 2005-2006. Panel B contrasts the crisis period plots (of Panel A(ii)) for banks whose linkages have low (below median) z-score, with banks whose linkages have high (above median) z-score.

Panel A

(i)



(ii)



Panel B

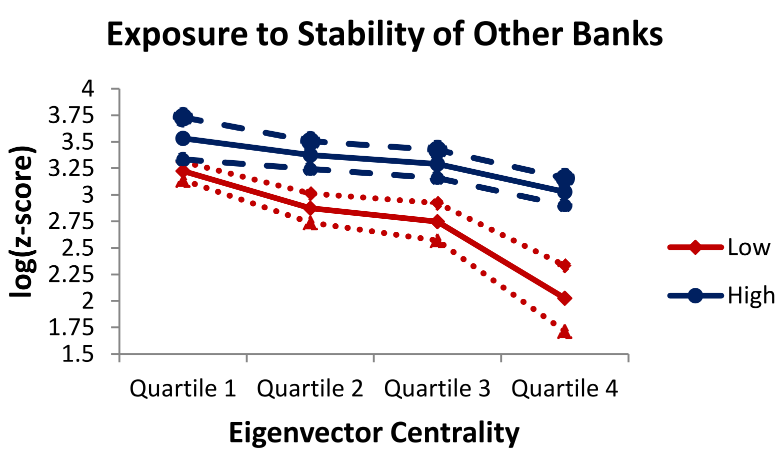
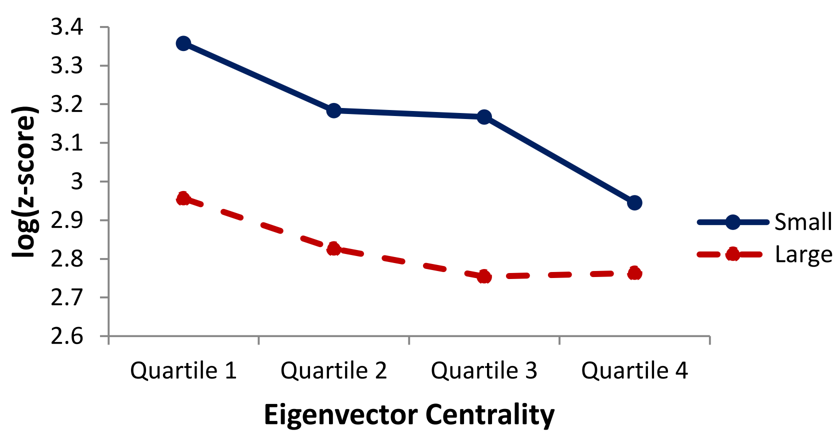


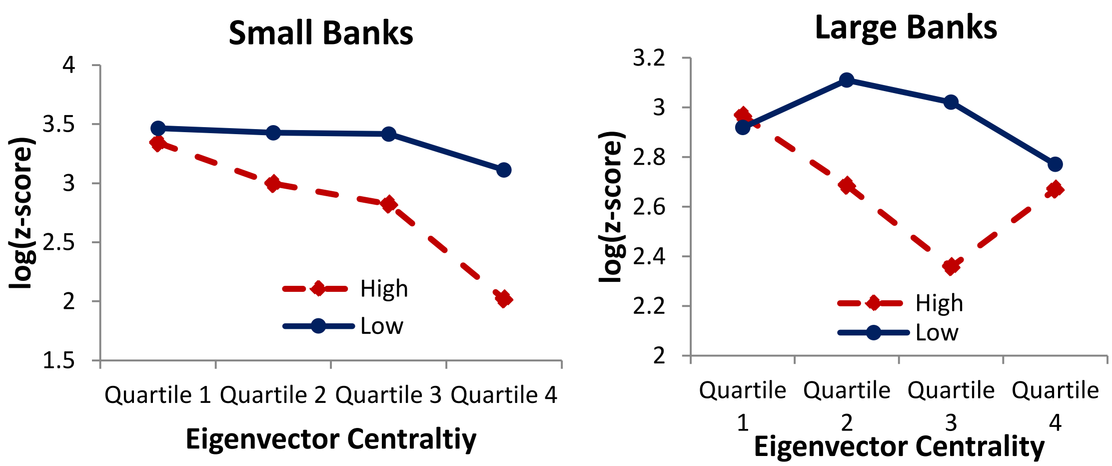
Figure 1-3. Amplifying Mechanisms

This figure plots the relationship between eigenvector centrality and stability for small (up to $1 billion in gross assets) and large banks (> $1 billion in gross assets) separately, and explores different mechanisms that affect this relationship. It plots means of crisis z-scores (logged values) for banks having centrality in different quartiles. Z-scores are computed over 2007-2009 and centrality scores are computed over 2005-2006. Panel A displays the relationship between centrality and z-scores in small versus large banks. Panel B displays how this relationship differs in banks connected to low (below median) versus high (above median) leverage banks. Panel C compares banks connected to those engaged in low versus high degree of securitization activity, while panel D compares banks connected to those having low versus high liquid holdings.

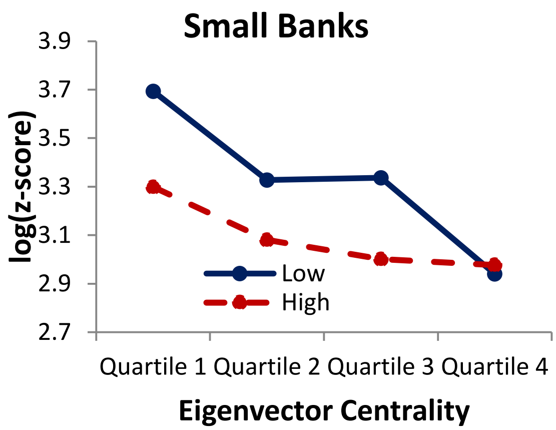
Panel A: Connectedness and Stability

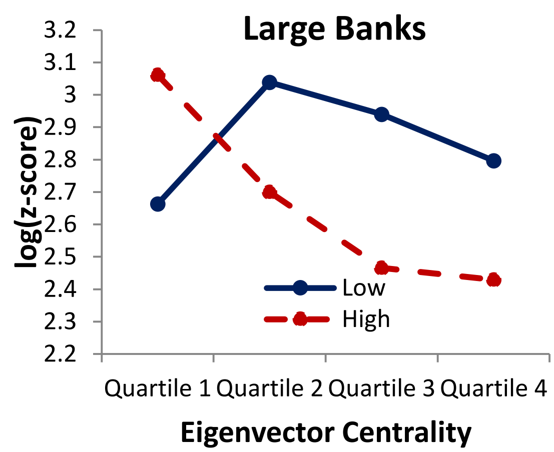


Panel B: Leverage of Other Banks

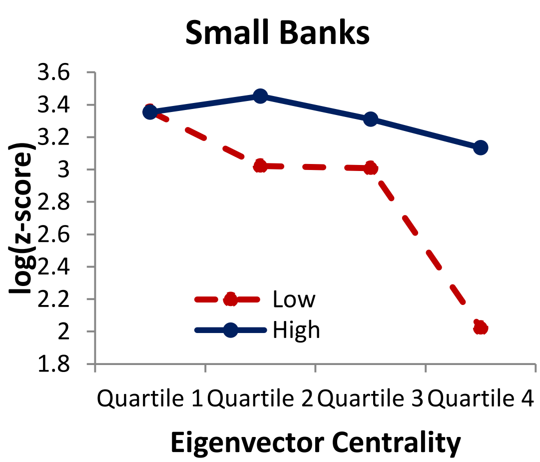


Panel C: Securitization Activity of Other Banks





Panel D: Liquid Holdings of Other Banks



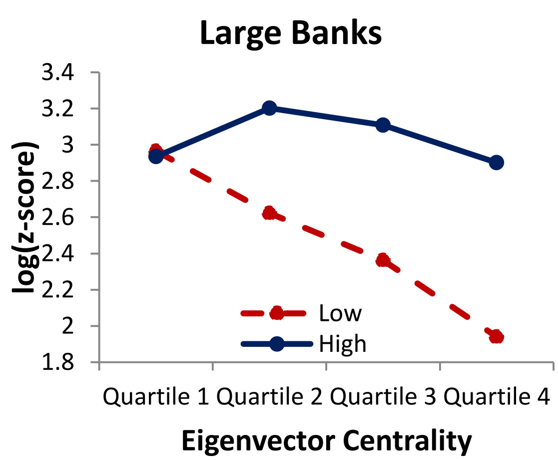


Table 1-1. Summary Statistics

Panel A presents summary statistics for all variables used in the regressions, and Panel B compares means and standard deviations for key variables of large (>$1bill GTA) and small banks (up to $1bill GTA). Panel B also reports t-test results for the difference in means between large and small banks. *** indicates statistical significance at 1% level.

Panel A

Variable	N	Mean	SD	Min	P25	Median	P75	Max
Dependent Variable								
log(Crisis Z-score)	1348	3.07	0.99	0.28	2.58	3.30	3.74	4.87
Main Independent Variable								
Eigenvector Centrality	1348	0.07	0.06	0.02	0.04	0.06	0.09	0.36
Control Variables								
log(Pre-crisis Z-score)	1348	3.53	0.50	2.31	3.19	3.47	3.80	4.88
Concentration Exposure	1348	0.14	0.04	0.08	0.11	0.13	0.16	0.29
Unemployment Exposure	1348	4.78	0.90	3.04	4.23	4.77	5.22	8.25
Home Price Changes	1348	0.08	0.05	0.00	0.04	0.07	0.11	0.21
log(Deposits)	1348	12.98	1.36	10.51	12.01	12.99	13.63	17.68
BHC	1348	0.59	0.49	0	0	1	1	1
Asset Quality	1348	0.01	0.01	0.00	0.00	0.00	0.01	0.04
Management Quality	1348	0.02	0.01	0.01	0.01	0.02	0.02	0.04

Panel B

	Small			Large			Small-Large
	N	Mean	Std. Dev	N	Mean	Std. Dev	Difference in Means
log(Crisis Z-score)	989	3.17	0.98	359	2.81	1	0.36***
log(Pre-crisis Z-score)	989	3.58	0.54	359	3.38	0.37	0.20***
Eigenvector Centrality	989	0.07	0.06	359	0.08	0.07	-0.01
Tier 1 Capital Ratio	989	0.16	0.07	359	0.12	0.05	0.04***
Fraction of Loans Sold	989	0.21	0.29	359	0.34	0.29	-0.13***
Liquidity Ratio	989	0.26	0.16	359	0.18	0.12	0.08***

Table 1-2. Z-scores and Connectedness

This table displays the relationship between connectedness during the pre-crisis period (2005-2006) and stability during the crisis period (2007-2009). Columns (1) through (3) report OLS regression estimates for equation (1), in which the dependent variable is *log(crisis z-score)*. Columns (4) through (6) report probit model results for equation (2), in which the dependent variable is an indicator variable identifying a high decline in z-score (% change in z-score from pre-crisis to crisis is smaller than the median for the sample). The main independent variable in both models is *Eigenvector Centrality*, which is given by the principal right eigenvector of the weighted adjacency matrix (see Figure 1). Columns (1) and (4) present results for the full sample, (2) and (5) present results for the large bank subsample (>$1bill gross assets), and columns (3) and (6) present results for the small bank subsample (up to $1bill gross assets). All control variables are computed as described in the text, and all independent variables are averaged over the pre-crisis period. Robust standard errors are reported in parenthesis. Finally, *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	log(crisis z-score)			High z-score decline		
	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample	Large	Small	Full Sample	Large	Small
Eigenvector Centrality	-1.359***	-0.44	-1.670***	1.813***	1.596	1.800**
	(0.404)	(0.755)	(0.485)	(0.619)	(1.214)	(0.730)
log(Pre-crisis Z-score)	0.482***	0.320*	0.508***	0.644***	0.792***	0.636***
	(0.059)	(0.171)	(0.064)	(0.081)	(0.219)	(0.088)
Concentration Exposure	-0.44	0.505	-0.307	-0.094	-1.764	0.032
	(0.558)	(1.245)	(0.635)	(0.905)	(1.974)	(1.045)
Unemployment exposure	-0.052*	-0.144**	-0.01	0.091**	0.249***	0.031
	(0.029)	(0.060)	(0.033)	(0.042)	(0.093)	(0.048)
Home Price Changes	-4.738***	-7.213***	-4.008***	4.646***	8.048***	3.671***
	(0.595)	(1.274)	(0.664)	(0.812)	(1.863)	(0.910)
log(Deposits)	-0.002	0.05	0.003	-0.032	-0.043	0.003
	(0.023)	(0.042)	(0.043)	(0.034)	(0.068)	(0.071)
BHC	-0.426***	-0.413**	-0.405***	0.527***	0.685***	0.463***
	(0.068)	(0.185)	(0.082)	(0.099)	(0.259)	(0.125)
Asset Quality	-12.544***	-34.236***	-8.775**	16.831***	51.525***	11.912**
	(3.261)	(8.151)	(3.469)	(5.275)	(13.817)	(5.622)
Management Quality	-1.492	11.617	-7.701	-2.03	-23.727*	6.075
	(4.448)	(8.646)	(5.280)	(6.159)	(12.892)	(7.301)
Constant	2.548***	2.622***	2.231***	-3.158***	-4.255***	-3.291***
	(0.420)	(0.971)	(0.640)	(0.611)	(1.436)	(1.020)
Observations	1348	359	989	1348	359	989
R-squared	0.219	0.166	0.23			
Pseudo R-sq				0.064	0.105	0.061

Table 1-3. Contagion

This table shows the effect of the riskiness of other banks in the stability of the subject bank. It presents estimates for the model in equation (3), in which exposure to stability of other banks is interacted with *Eigenvector Centrality*. Results are presented for the OLS regression model, in which the dependent variable is *log(crisis z-score)*(measured over 2007-2009), and the probit model, in which the dependent variable is an indicator variable identifying a high decline in z-score (% change in z-score from pre-crisis to crisis is smaller than the median for the sample). The main independent variable in both models is *Eigenvector Centrality,* which is measured during the pre-crisis period of 2005-2006 and is given by the principal right eigenvector of the weighted adjacency matrix (see Figure 1). Panel A presents results for the full sample, large bank subsample (>$1bill GTA), and small bank subsample (up to $1bill GTA). *Dummy High Other Zscore* is an indicator identifying banks whose linkages have above median z-score. Panel B breaks full sample into banks having above median (high) pre-crisis z-score and those having below median (low) pre-crisis z-score. Panel C considers linkages to risky (banks having z-score in the lowest quartile) versus stable banks (banks having z-score in the highest quartile) separately. All other control variables are computed as described in the text, and all independent variables are averaged over the pre-crisis period. Robust standard errors are reported in parenthesis. Finally, *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

Panel A	log(crisis z-score)			High z-score decline		
	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample	Large	Small	Full Sample	Large	Small
Eigenvector Centrality	-12.908***	-10.168***	-13.560***	15.029***	19.058***	14.190***
	(1.443)	(2.673)	(1.686)	(2.228)	(4.778)	(2.543)
Eigenvector Centrality * Dummy High Other Zscore	11.746***	9.966***	11.996***	-13.481***	-18.646***	-12.273***
	(1.502)	(2.769)	(1.770)	(2.322)	(4.916)	(2.675)
Dummy High Other Zscore	-0.339***	-0.383**	-0.272***	0.420***	1.020***	0.21
	(0.088)	(0.176)	(0.102)	(0.146)	(0.309)	(0.169)
Controls	Y	Y	Y	Y	Y	Y
Observations	1348	359	989	1348	359	989
R-squared	0.27	0.194	0.294			
Pseudo R-squared				0.088	0.135	0.09

Panel B

	log(crisis z-score)		High z-score decline	
	(1)	(2)	(3)	(4)
	High Pre-Zscore	Low Pre-Zscore	High Pre-Zscore	Low Pre-Zscore
Eigenvector Centrality	-9.825***	-14.243***	6.363*	21.457***
	(2.437)	(1.802)	(3.407)	(2.989)
Eigenvector Centrality * Dummy High Other Zscore	9.785***	12.521***	-6.774*	-18.553***
	(2.500)	(1.890)	(3.548)	(3.115)
Dummy High Other Zscore	-0.236*	-0.373***	0.121	0.602***
	(0.134)	(0.116)	(0.211)	(0.208)
Controls	Y	Y	Y	Y
Observations	674	674	674	674
R-squared	0.196	0.232		
Pseudo R-squared			0.08	0.123

Panel C

	Links to Risky Banks		Links to Stable banks	
	(1)	(2)	(3)	(4)
	log(crisis z-score)	High z-score decline	log(crisis z-score)	High z-score decline
Eigenvector Centrality	-1.672***	2.013***	0.089	-0.03
	(0.385)	(0.590)	(0.099)	(0.160)
Controls	Y	Y	Y	Y
Observations	1348	1348	1346	1346
R-squared	0.225		0.213	
Pseudo R-squared		0.066		0.062

Table 1-4. Amplifying Mechanism: Leverage of Other Banks

This table shows the effect of the leverage of other banks on the relationship between connectedness (measured during the pre-crisis period of 2005-2006) and stability (measured during the crisis period of 2007-2009). It provides estimates for the model in equation (3). Columns (1) through (3) report OLS regression results, in which the dependent variable is *log(crisis z-score)*. Columns (4) through (5) report probit model results, in which the dependent variable is an indicator variable identifying a high decline in z-score (% change in z-score from pre-crisis to crisis is smaller than the median for the sample). Columns (1) and (4) present results for the whole sample, (2) and (5) present results for the large bank subsample (>$1bill GTA), and columns (3) and (6) present results for the small bank subsample (up to $1bill GTA) respectively. The main independent variable in both models is *Eigenvector Centrality,* which is given by the principal right eigenvector of the weighted adjacency matrix (see Figure 1). *Dummy High Other Leverage* is an indicator identifying banks whose linkages have above median Tier 1 risk-based capital ratio. All other control variables are computed as described in the text, and all independent variables are averaged over the pre-crisis period. Robust standard errors are reported in parenthesis. Finally, *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	log(crisis z-score)			High z-score decline		
	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample	Large	Small	Full Sample	Large	Small
Eigenvector Centrality	-1.058**	-0.646	-1.242**	1.024	0.681	1.106
	(0.423)	(0.797)	(0.509)	(0.670)	(1.270)	(0.809)
Eigenvector Centrality * Dummy High Other Tier 1 Leverage	-11.461***	-8.754***	-12.097***	14.085***	17.834***	13.524***
	(1.509)	(3.339)	(1.689)	(2.285)	(5.554)	(2.526)
Dummy High Other Tier 1 Leverage	0.379***	0.196	0.392***	-0.620***	-0.940***	-0.520***
	(0.086)	(0.183)	(0.097)	(0.144)	(0.320)	(0.164)
Controls	Y	Y	Y	Y	Y	Y
Observations	1348	359	989	1348	359	989
R-squared	0.265	0.195	0.287			
Pseudo R-squared				0.086	0.129	0.085

Table 1-5. Amplifying Mechanism: Securitization Activity of Other Banks

This table shows the effect of securitization activity of other banks on the relationship between connectedness (measured during the pre-crisis period of 2005-2006) and stability (measured during the crisis period of 2007-2009). It provides estimates for the model in equation (3). Columns (1) through (3) report OLS regression results, in which the dependent variable is *log(crisis z-score)*. Columns (4) through (5) report probit model results, in which the dependent variable is an indicator variable identifying a high decline in z-score (% change in z-score from pre-crisis to crisis is smaller than the median for the sample). Columns (1) and (4) present results for the whole sample, (2) and (5) present results for the large bank subsample (>$1bill GTA), and columns (3) and (6) present results for the small bank subsample (up to $1bill GTA) respectively. The main independent variable in both models is *Eigenvector Centrality*, which is given by the principal right eigenvector of the weighted adjacency matrix (see Figure 1). *Dummy High Other Securitization* is an indicator identifying banks whose linkages have above median level of securitization activity. All other control variables are computed as described in the text, and all independent variables are averaged over the pre-crisis period. Robust standard errors are reported in parenthesis. Finally, *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	log(crisis z-score)			High z-score decline		
	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample	Large	Small	Full Sample	Large	Small
Eigenvector Centrality	-1.062**	-0.546	-1.316**	1.235*	1.106	1.292
	(0.434)	(0.803)	(0.526)	(0.675)	(1.262)	(0.816)
Eigenvector Centrality * Dummy High Other Securitization	-5.998***	-7.869**	-4.937***	6.386***	12.441**	4.074
	(1.592)	(3.295)	(1.801)	(2.386)	(5.603)	(2.731)
Dummy High Other Securitization	0.261***	0.15	0.245**	-0.370**	-0.535	-0.273
	(0.094)	(0.195)	(0.107)	(0.149)	(0.331)	(0.173)
Controls	Y	Y	Y	Y	Y	Y
Observations	1348	359	989	1348	359	989
R-squared	0.228	0.195	0.236			
Pseudo R-squared				0.068	0.122	0.063

Table 1-6. Mitigating Mechanism: Liquid Holdings of Other Banks

This table shows the effect of liquid holdings of other banks on the relationship between connectedness (measured during the pre-crisis period of 2005-2006) and stability (measured during the crisis period of 2007-2009). It provides estimates for the model in equation (3). Columns (1) through (3) report OLS regression results, in which the dependent variable is *log(crisis z-score)*. Columns (4) through (5) report probit model results, in which the dependent variable is an indicator variable identifying a high decline in z-score (% change in z-score from pre-crisis to crisis is smaller than the median for the sample). Columns (1) and (4) present results for the whole sample, (2) and (5) present results for the large bank subsample (>$1bill GTA), and columns (3) and (6) present results for the small bank subsample (up to $1bill GTA) respectively. The main independent variable in both models is *Eigenvector Centrality*, which is given by the principal right eigenvector of the weighted adjacency matrix (see Figure 1). *Dummy High Other Liquidity* is an indicator identifying banks whose linkages have above median level of liquid holdings. All other control variables are computed as described in the text, and all independent variables are averaged over the pre-crisis period. Robust standard errors are reported in parenthesis. Finally, *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	log(crisis z-score)			High z-score decline		
	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample	Large	Small	Full Sample	Large	Small
Eigenvector Centrality	-11.507***	-10.629***	-11.619***	13.770***	20.853***	11.980***
	(1.402)	(2.664)	(1.662)	(2.074)	(4.773)	(2.328)
Eigenvector Centrality * Dummy High Other Liquidity	10.371***	9.766***	10.384***	-12.756***	-19.756***	-11.073***
	(1.443)	(2.741)	(1.718)	(2.156)	(4.910)	(2.437)
Dummy High Other Liquidity	-0.341***	-0.116	-0.387***	0.620***	0.852***	0.567***
	(0.084)	(0.171)	(0.097)	(0.141)	(0.308)	(0.161)
Controls	Y	Y	Y	Y	Y	Y
Observations	1348	359	989	1348	359	989
R-squared	0.261	0.231	0.27			
Pseudo R-squared				0.083	0.143	0.076

Table 1-7. Placebo Event

This table conducts a placebo test in which 2005-2006 is used as the false crisis period and 2003-2004 is used as the relevant pre-crisis period. Columns (1) through (5) report OLS regression results, in which the dependent variable used is *log(false crisis z-score)*, whereas columns (6) through (10) report results for the probit model, in which the dependent variable is an indicator variable identifying a high decline in z-score (% change in z-score from pre-crisis to crisis is smaller than the median for the sample). The main independent variable in both models is *Eigenvector Centrality*, which is given by the principal right eigenvector of the weighted adjacency matrix (see Figure 1). Results are presented for the full sample only. *Dummy High Other Zscore* is an indicator identifying banks whose linkages have above median level of zscore. *Dummy High Other Tier 1 Leverage*, *Dummy High Other Securitization*, and *Dummy High Other Liquidity* are defined similarly. All other control variables are computed as described in the text, and all independent variables are averaged over the pre-crisis period. Robust standard errors are reported in parenthesis. Finally, *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	log(false crisis z-score)					High z-score decline				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Eigenvector Centrality	-0.117	0.521	-0.143	-0.107	0.013	0.138	-2.691	0.359	0.249	-2.399
	(0.088)	(0.599)	(0.091)	(0.092)	(0.768)	(0.285)	(2.049)	(0.295)	(0.296)	(2.345)
Eigenvector Centrality * Dummy High Other Zscore		-0.693					3.068			
		(0.610)					(2.067)			
Eigenvector Centrality * Dummy High Other Tier 1 Leverage			0.275					-2.491		
			(0.654)					(1.987)		
Eigenvector Centrality * Dummy High Other Securitization				-0.084					-2.032	
				(0.466)					(1.784)	
Eigenvector Centrality * Dummy High Other Liquidity					-0.171					2.814
					(0.780)					(2.363)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2029	2029	2029	2029	2029	2029	2029	2029	2029	2029
R-squared	0.48	0.482	0.481	0.48	0.481					
Pseudo R-squared						0.057	0.06	0.06	0.058	0.061

Table 1-8. Placebo Linkages

This table presents results for the study around the 2007 crisis using placebo linkages. Specifically, it presents results for the sample of banks that sell all of the loans that they originate in a given MSA. Columns (1) through (4) report OLS regression results, in which the dependent variable used is *log(crisis z-score)*. Columns (5) through (8) report probit model results, in which the dependent variable is an indicator variable identifying a high decline in z-score (% change in z-score from pre-crisis to crisis is smaller than the median for the sample). The main independent variable is *Eigenvector Centrality*, which is given by the principal right eigenvector of the weighted adjacency matrix (see Figure 1). Results are presented for the full sample only. *Dummy High Other Zscore* is an indicator identifying banks whose linkages have above median level of zscore. *Dummy High Other Leverage* and *Dummy High Other Liquidity* are defined similarly. All other control variables are computed as described in the text, and all independent variables are averaged over the pre-crisis period. Robust standard errors are reported in parenthesis. Finally, *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	log(crisis z-score)				High z-score decline			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Eigenvector Centrality	-0.543	-0.646	-0.868	-0.672	0.955	1.055	0.982	1.524
	(0.395)	(0.563)	(0.595)	(0.602)	(0.620)	(0.829)	(0.859)	(1.001)
Eigenvector Centrality * Dummy High Other Zscore		0.124				-0.184		
		(0.704)				(1.087)		
Eigenvector Centrality * Dummy High Other Tier 1 Leverage			0.545				0.033	
			(0.727)				(1.097)	
Eigenvector Centrality * Dummy High Other Liquidity				-0.03				-0.463
				(0.749)				(1.184)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	534	534	534	534	535	535	535	535
R-squared	0.082	0.095	0.085	0.085				
Pseudo R-squared					0.077	0.079	0.078	0.08

Table 1-9. Exposure to Common Market Conditions

This table presents the implications of bubble market exposure on the relationship between pre-crisis connectedness and crisis stability. Bubble markets are MSAs that have price-to-income ratio in the top quartile of the distribution for the sample. Columns (1)-(4) present OLS results, in which the dependent variable is *log(crisis z-score)*; columns (5)-(8) present results for the probit model, in which the dependent variable is a dummy variable for high decline in z-score (% change in z-score from pre-crisis to crisis is smaller than the median for the sample). The main independent variable is *Eigenvector Centrality (EC)*, which is given by the principal right eigenvector of the weighted adjacency matrix. Columns (1) and (5) include interactions between *EC* and indicator variables that identify banks with bubble market exposure at different quartiles of the distribution for the sample. *Bubble Market Exp in 2nd Quartile* identifies banks having bubble market exposure in the 2nd Quartile. Other indicator variables are defined similarly, and banks in the 1st Quartile serve as the base group. Columns (2) and (6) presents results for banks having no exposure to bubble markets; columns (3) and (4) present results for those having full exposure; columns (4) and (8) present results for 166 random banks from the no exposure sample. All control variables are computed as described in the text, and all independent variables are averaged over the pre-crisis period. Robust standard errors are reported in parenthesis. Finally, *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	log(crisis z-score)				High z-score decline			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full Sample	No Exp	Full Exp	No Exp (random)	Full Sample	No Exp	Full Exp	No Exp (random)
Eigenvector Centrality (EC)	-8.827***	-7.904***	0.785	-9.486***	9.686***	9.402***	-1.365	15.646***
	(1.901)	(1.913)	(0.767)	(2.711)	(2.582)	(2.654)	(1.417)	(4.288)
EC * Bubble Market Exp in 2nd Quartile	1.445				0.516			
	(3.622)				(5.477)			
EC * Bubble Market Exp in 3rd Quartile	6.395***				-6.810**			
	(2.005)				(2.779)			
EC * Bubble Market Exp in 4th Quartile	9.544***				-10.465***			
	(1.956)				(2.710)			
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1348	490	166	166	1348	490	166	166
R-squared	0.244	0.255	0.329	0.288				
Psuedo R-squared					0.078	0.078	0.09	0.125

Table 1-10. Placebo Linkages (with exposure to market conditions)

This table presents results for the study around the 2007 crisis using placebo linkages that still capture the subject bank's exposure to market conditions. Specifically, this test considers linkages from banks that engage in portfolio lending in a given MSA to banks that sell all of the loans they originate in that MSA. Columns (1) through (4) report OLS regression results, in which the dependent variable is *log(crisis z-score)*. Columns (5) through (8) report probit model results, in which the dependent variable is an indicator variable identifying a high decline in z-score (% change in z-score from pre-crisis to crisis is smaller than the median for the sample). Results are presented for the full sample only. The main independent variable is *Eigenvector Centrality*, which is given by the principal right eigenvector of the weighted adjacency matrix (see Figure 1). *Dummy High Other Zscore* is an indicator identifying banks whose linkages have above median level of zscore. *Dummy High Other Leverage* and *Dummy High Other Liquidity* are defined similarly. All other control variables are computed as described in the text, and all independent variables are averaged over the pre-crisis period. Robust standard errors are reported in parenthesis. Finally, *, ** and *** indicate significance at 10%, 5%, and 1% level respectively.

	log(crisis z-score)				High z-score decline			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Eigenvector Centrality (EC)	-3.467***	-2.524***	-4.672***	-4.210***	2.528***	1.952*	2.899**	3.667***
	(0.605)	(0.699)	(1.089)	(0.824)	(0.827)	(1.005)	(1.472)	(1.144)
EC * Dummy High Other Zscore		-2.248**				1.15		
		(1.026)				(1.403)		
EC * Dummy High Other Tier 1 Leverage			1.714				-0.724	
			(1.184)				(1.598)	
EC * Dummy High Other Liquidity				1.107				-1.846
				(1.034)				(1.432)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1364	1364	1364	1364	1364	1364	1364	1364
R-squared	0.238	0.244	0.24	0.241				
Pseudo R-squared					0.071	0.074	0.072	0.073

Table 1-11. Exclusion of the Top 1 Percentile Bubble Markets

This table presents results for the study around the 2007 crisis for a subsample of banks that do not originate mortgages in MSAs that have price-to-income ratio greater than the top 1 percentile level for the sample. Columns (1) through (5) report OLS regression results, in which the dependent variable used is *log(crisis z-score),* whereas columns (6) through (10) report results for the probit model, in which the dependent variable is an indicator variable identifying a high decline in z-score (% change in z-score from pre-crisis to crisis is smaller than the median for the sample). The main independent variable in both models is *Eigenvector Centrality (EC)*, which is given by the principal right eigenvector of the weighted adjacency matrix (see Figure 1). *High Other Zscore* is an indicator identifying banks whose linkages have above median level of zscore. *High Other Tier 1 Leverage*, *High Other Securitization*, and *High Other Liquidity* are defined similarly. All other control variables are computed as described in the text, and all independent variables are averaged over the pre-crisis period. Robust standard errors are reported in parenthesis. Finally, *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	log(crisis z-score)					High z-score Decline				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
EC	-1.327***	-12.493***	-1.033**	-1.045**	-11.337***	1.751***	14.695***	0.998	1.234*	13.352***
	(0.407)	(1.461)	(0.426)	(0.438)	(1.422)	(0.620)	(2.253)	(0.674)	(0.680)	(2.096)
EC * High Other Zscore		11.373***					-13.170***			
		(1.522)					(2.350)			
EC * High Other Tier 1 Leverage			-11.452***					14.118***		
			(1.524)					(2.315)		
EC * High Other Securitization				-5.720***					5.994**	
				(1.591)					(2.403)	
EC * High Other Liquidity					10.238***					-12.420***
					(1.464)					(2.178)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1291	1291	1291	1291	1291	1291	1291	1291	1291	1291
R-squared	0.224	0.273	0.272	0.233	0.266					
Pseudo R-sq						0.062	0.087	0.085	0.066	0.08

Table 1-12. Public Bank Subsample

This table presents results for the relationship between connectedness and stability around the 2007 crisis for a subsample of public banks. The dependent variables used are overall market risk and idiosyncratic risk during the crisis period. Overall market risk is computed as the standard deviation of stock return. Idiosyncratic risk is computed as the standard deviation of the residuals obtained from estimating the following equation for each bank: $r_{i,t} = \alpha_i + \beta_{1,i}\, r_{m,t} + \beta_{2,i}\Delta\,(Baa - Aaa)_t + \beta_{3,i}\,\Delta(3 - month\,T - bill)_t + \epsilon_{i,t}$ where $r_{m,t}$ is weekly S&P 500 market return, $\Delta(Baa - Aaa)_t$ is default risk factor (change in difference between yields on *Baa* and *Aaa* rated corporate bonds), and $\Delta(3 - month\,T - bill)_t$ is interest risk factor (change in the yield of 3-month treasury bill). The main independent variable is *Eigenvector Centrality*, which is given by the principal right eigenvector of the weighted adjacency matrix (see Figure 1). *Dummy High Other Zscore* is an indicator identifying banks whose linkages have above median level of zscore. *Dummy High Other Tier 1 Leverage/Securitization/Liquidity* are defined similarly. All other control variables are computed as described in the text, and all independent variables are averaged over the pre-crisis period. Robust standard errors are reported in parenthesis. Finally, *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	Overall Market Risk (crisis)					Idiosyncratic Risk (crisis)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Eigenvector Centrality (EC)	0.056**	0.492***	0.052*	0.049*	0.457***	0.060**	0.495***	0.055**	0.055*	0.466***
	(0.028)	(0.123)	(0.027)	(0.029)	(0.124)	(0.027)	(0.118)	(0.027)	(0.028)	(0.119)
EC * Dummy High Other Zscore		-0.490***					-0.487***			
		(0.125)					(0.120)			
EC * Dummy High Other Tier 1 Leverage			0.471***					0.467***		
			(0.131)					(0.127)		
EC * Dummy High Other Securitization				0.176					0.159	
				(0.132)					(0.132)	
EC * Dummy High Other Liquidity					-0.384***					-0.392***
					(0.125)					(0.120)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	273	273	273	273	273	273	273	273	273	273
R-squared	0.193	0.239	0.247	0.201	0.264	0.157	0.208	0.215	0.166	0.233

Table 1-13. Linkages Less Likely to be Broken

This table presents results for the study around the 2007 crisis using linkages based on subprime and jumbo loans only. These two types of loans were not purchased by Fannie Mae and Freddie Mac (primary buyers of home loans) during the crisis period, so the linkages that they represent are less likely to be broken. Columns (1) through (4) report OLS regression results, in which the dependent variable is *log(crisis z-score)*, whereas columns (5) through (8) report results for the probit model, in which the dependent variable is an indicator variable identifying a high decline in z-score (% change in z-score from pre-crisis to crisis is smaller than the median for the sample). The main independent variable in both models is *Eigenvector Centrality*, which is given by the principal right eigenvector of the weighted adjacency matrix (see Figure 1). *Dummy High Other Zscore* is an indicator identifying banks whose linkages have above median level of zscore. *Dummy High Other Tier 1 Leverage* and *Dummy High Other Liquidity* are defined similarly. All other control variables are computed as described in the text, and all independent variables are averaged over the pre-crisis period. Robust standard errors are reported in parenthesis. Finally, *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	log(crisis z-score)				High Decline in Z-score			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Eigenvector Centrality (EC)	-0.201	-9.550***	-0.215	-8.112***	0.193	13.638***	0.146	10.528***
	(0.252)	(1.545)	(0.262)	(1.559)	(0.384)	(2.525)	(0.402)	(2.367)
EC * Dummy High Other Zscore		9.210***				-13.422***		
		(1.545)				(2.522)		
EC * Dummy High Other Tier 1 Leverage			-8.694***				11.119***	
			(1.596)				(2.553)	
EC * Dummy High Other Liquidity				7.637***				-10.100***
				(1.554)				(2.359)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1021	1021	1021	1021	1022	1022	1022	1022
R-squared	0.197	0.232	0.221	0.236				
Pseudo R-squared					0.071	0.094	0.086	0.093

Table 1-14. Policy Implications

Panel A of this table presents the impact of Tier 1 capital ratio, Total capital ratio, and liquidity ratio of *other* banks on the relationship between connectedness (during 2005-2006) and stability (during 2007-2009) of the subject bank. Results are presented for the full sample and for the OLS model, in which the dependent variable is *log(crisis z-score)*. The main independent variable is *Eigenvector Centrality*, which is given by the principal right eigenvector of the weighted adjacency matrix. *Other Tier 1 Capital Ratio in 2nd Quintile* identifies banks whose linkages have Tier 1 capital ratio in the 2nd quintile. Other indicator variables are defined similarly to identify banks whose linkages have capital and liquidity ratios in different quintiles. Quintile 1 serves as the base group. Panel B presents the impact of subject bank's own capital and liquidity ratios in the relationship between connectedness and stability. *High Tier 1 Capital Ratio* identifies banks having above median Tier 1 capital ratio. *High Total Capital Ratio* and *High Liquidity Ratio* are defined similarly. Results are presented for the full sample, and for OLS as well as the probit model, in which the dependent variable is an indicator variable identifying a high decline in z-score (% change in z-score from pre-crisis to crisis is smaller than the median for the sample). All control variables are computed as described in the text. All independent variables are averaged over the pre-crisis period. Robust standard errors are reported in parenthesis. Finally, *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

Panel A	log(crisis z-score)		
	(1)	(2)	(3)
Eigenvector Centrality (EC)	-18.820***	-14.982***	-22.946***
	(4.687)	(3.706)	(3.167)
EC * Other Tier1 Capital Ratio in 2nd Quintile	5.886		
	(5.256)		
EC * Other Tier1 Capital Ratio in 3rd Quintile	4.602		
	(5.040)		
EC * Other Tier1 Capital Ratio in 4th Quintile	17.696***		
	(4.716)		
EC * Other Tier1 Capital Ratio in 5th Quintile	18.023***		
	(4.755)		
EC * Other Total Capital Ratio in 2nd Quintile		-0.287	
		(4.090)	
EC *Other Total Capital Ratio in 3rd Quintile		6.21	
		(4.106)	
EC * Other Total Capital Ratio in 4th Quintile		14.179***	
		(3.728)	
EC * Other Total Capital Ratio in 5th Quintile		13.627***	
		(3.933)	
EC * Other Liquidity Ratio in 2nd Quintile			10.736***
			(3.748)
EC * Other Liquidity Ratio in 3rd Quintile			18.015***
			(3.743)
EC * Other Liquidity Ratio in 4th Quintile			22.033***
			(3.195)
EC * Other Liquidity Ratio in 5th Quintile			22.940***
			(3.367)
Controls	Y	Y	Y
Observations	1348	1348	1348
R-squared	0.284	0.286	0.281

Panel B

	log(crisis z-score)			High Decline in Z-score		
	(1)	(2)	(3)	(4)	(5)	(6)
Eigenvector Centrality (EC)	-1.778***	-1.730***	-1.281**	2.519***	2.841***	2.002**
	(0.535)	(0.511)	(0.560)	(0.857)	(0.880)	(0.888)
EC * Dummy High Tier 1 Capital Ratio	0.783			-1.285		
	(0.776)			(1.220)		
EC * Dummy High Total Capital Ratio		0.704			-1.993	
		(0.787)			(1.223)	
EC * Dummy High Liquidity Ratio			-0.333			-0.119
			(0.784)			(1.208)
Controls	Y	Y	Y	Y	Y	Y
Observations	1348	1348	1348	1348	1348	1348
R-squared	0.238	0.234	0.237			
Pseudo R-squared				0.079	0.077	0.075

Chapter 2

The Impact of Liquidity Requirements on Loan Contract Terms

2.1 Introduction

In the aftermath of the 2007 financial crisis, Basel III introduced two new liquidity requirements, along with higher capital standards. While capital requirements seek to encourage banks to reduce risk taking by holding enough capital, liquidity requirements were introduced to ensure that banks reduce their exposure to liquidity risk by holding enough liquid assets and enough stable funding to withstand a period of economic stress.

The events of the crisis revealed how excessive liquidity risk, which banks take by originating illiquid loans while funding them with liquid deposits, can increase the risk of run in the case of an unexpected shock, and how it can lead banks to fire-sell assets, or drive them to insolvency.[47] It was also evident how fire-sale of assets and failure of banks have further spillover effects on other financial institutions. While deposit insurance and the use of lender-of-last-resort capacity of the central bank can mitigate such adverse consequences of liquidity risk, these two approaches are socially costly and could encourage moral hazard on banks ex-ante (House, Sablik, and Walter (2016), Stein (2013)). Recognizing these shortcomings, Basel III introduced new liquidity requirements.

In order to understand whether liquidity requirements are working well to attain policy goals of improving the resilience of the banking system, we need to understand how this rule is affecting bank behavior. To that end, we study how banks change loan

[47] Bryant (1980) and Diamond and Dybvig (1983) formalize in a theoretical model how liquidity risk can increase the risk of run.

contract terms in response to the introduction of one of the liquidity requirements – the Liquidity Coverage Ratio (LCR) rule. This rule requires that banks hold enough liquid assets to withstand an unexpected cash outflow in a standardized 30-day stress scenario.[48] This study further sheds light on how this rule affects borrowers. Any impact on loan contract terms has implications for the financial condition of the borrowers, which has further consequences on the growth of the real economy.

Theory provides conflicting predictions on the consequences of these liquidity requirements. Bouwman (2013) suggests that we cannot study these requirements in isolation, and that in order to deduce their consequences, we first need to understand the theoretical underpinnings of how these requirements might interact with capital requirements. Calomiris, Heider, and Hoerova (2013) suggest that liquidity and capital requirements may act as substitutes, which implies that liquidity requirements are potentially costly for banks. On the other hand, Acharya, Mehran and Thakor (2013) argue that the two requirements act as complements such that both of them are beneficial for banks. In that case, banks may be able to obtain cheaper funding from investors. Depending on whether liquidity requirements are costly or beneficial, banks may tighten or loosen lending terms for borrowers. If the requirements are costly, it is likely that banks will pass these costs down to borrowers.

In order to estimate the effect of LCR on loan contract terms, we employ a differences-in-differences method, in which we compare changes in contract terms by treated banks (banks required to comply) around the LCR event, with similar changes in contract terms by control banks (banks not required to comply). Only banks having greater than or equal to $50 billion in assets are subject to this rule. Among them, the largest set of banks had to comply in January 2015, while others were required to comply only a year later.[49] Such timing for implementation of LCR provides a setting with two different events to estimate the impact of the requirement, and, thus, allows for a more robust study.

[48]This rule requires that the ratio of high quality liquid assets to expected cash outflow be maintained at 100%. See section III for further details.

[49] See Section III for more details on this rule, its implementation, and the events surrounding this event.

We use data on syndicate loans from the Dealscan database for our study. This database allows us to study loan contract terms in several dimensions. In particular, we use loan spread to study price implications of LCR, and we choose size and maturity of a loan to study how banks change their risk exposure. Additionally, we study the probability that a loan requires collateral, and the count of covenants (covenant intensity index ranging in value from 0 to 6) included in new loan issues to gauge how banks adjust their monitoring technologies. While we do not find evidence of impact on spread, loan size, maturity, or covenant index, we find statistically and economically significant effects on the probability that collateral is required on loans after the implementation of LCR rule. Specifically, we find that the probability that collateral is required increases by 16.7%.

These results indicate that the LCR rule prompts banks to hedge against payment defaults by putting better monitoring technologies in place. This is likely because banks now have to set aside assets that could have earned returns elsewhere, and this incentivizes them to reduce risk taking in new investments and ensure payments back from the borrowers. However, there is no evidence that the rule imposes high enough costs to increase pricing terms for the borrowers.

In order to further investigate possible costs imposed by LCR, we compare loan issues from banks that are expected to find the new rule more costly ex-ante with those that are expected to find it comparatively less costly. Specifically, banks having low liquidity ratios (the ratio of cash to deposits as used by Duchin and Sosyura (2014)) are expected to find the new rule more costly. However, we do not find any change in pricing terms by these banks, although they reduce their loan exposure by decreasing loan size. On the other hand, we find that banks with high liquidity lower loan spreads by 80.5 basis points and increase maturity by 12.7%. They combine such favorable contract terms with increased monitoring technologies by increasing the probability of collateral requirement by 29.8% and the number of covenants by 1.29. These results are indicative of cost savings for lenders with high liquidity, who then pass these savings down to borrowers by offering them lower spreads. That there is no price response from low liquidity banks is further indicative of modest costs of LCR to lenders. However, the LCR rule does incentivize both groups of banks to reduce risk exposure by increasing monitoring technologies or by downsizing the amount of loan issues.

We then ask whether bank behavior is different for different types of borrowers. In particular, we study whether relationship strength with the borrower affects how banks set loan contract terms. Relationship lending leads to information production, which can either benefit borrowers due to improved exchange of information or expose them to hold-up costs because of the information advantage that the current bank has over new banks. Our results suggest that prior to the introduction of the LCR rule, borrowers having stronger relationship with banks used to enjoy lower spreads compared to those having weaker such relationship. However, banks increase spreads for relationship borrowers post LCR such that there are no net benefits to relationships. On the other hand, there are no changes on loan spreads for borrowers having weak relationship with the banks. As before, this rule does incentivize banks to reduce their risk exposure to borrowers with weaker relationship (and thus little prior information on borrower activity) by increasing collateral requirements.

Finally, we conduct a placebo test, in which we assume that the LCR rule went into effect a year prior to the actual implementation date. We do not find any statistically significant impact on any of the loan contract terms, which lends support to the argument that the results just discussed are attributable to the event of the LCR rule.

Our paper adds to the new literature that studies the impact of liquidity requirements on different aspects of banking. Because liquidity regulation is new, empirical research in this area is limited. Banerjee and Mio (2017) study the implications of Individual Liquidity Guidance (ILG) in UK. ILG is similar in design to LCR, and the authors estimate its effects on the composition and size of banks' balance sheets. The paper finds that banks increase the share of high quality liquid assets and non-financial deposits, and decrease the share of intra-financial deposits and wholesale funding. However, there is no evidence that they decrease their balance sheet size or lending. The authors also estimate effects on the average interest rates that banks pay on non-financial loans as reported in their balance sheet. Similar to our results on loan pricing terms, they find no evidence of any increase in such rates. Our paper is different from theirs in that we use data on individual loans to study pricing impact, rather than use data on average price charged on all loans. This also allows us to explore the impact of LCR along several dimensions of loan characteristics, and because we have individual borrower information, we are able to conduct this study at different dimensions of borrower characteristics as well.

Other related studies include de Haan and van den End (2013), who study Dutch banks that were subject to liquidity regulation similar to LCR. They find that most banks hold more liquid assets than that required by regulation, implying potential benefits arising from liquid holdings. Hong, Huang, and Wu (2014) construct an approximate measure of liquidity coverage ratio from bank balance sheet data, and show that this measure is positively related with the probability of a bank failure, implying potential costs associated with the rule.

Theoretical work pertaining to liquidity regulation is also limited (see Allen (2014) for a survey). Rochet (2004) studies moral hazard issues arising from expectations of bailouts in case of macro shocks, and provides a theoretical justification for a regulation similar to a liquidity requirement to address such issues. The paper argues that such regulation should be dependent on macro exposures of each bank. Perotti and Suarez (2011) study externalities of short term funding, and argue that a combination of Pigovian taxes and net funding ratios can address such externality issues. However, they argue that liquidity ratio requirements like LCR are ineffective in addressing these issues. Another related paper is Keister and Bech (2012), which sheds light on how liquidity requirements may affect the implications of monetary policies, and suggests that monetary policies might need to be adjusted once liquidity regulation is in place.

The rest of the paper is organized as follows. Section II develops hypothesis. Section III describes the setting and events surrounding the introduction of the LCR rule. Section IV discusses methods, while section V describes data and variables. Section VI discusses the main empirical results of the paper, and section VII concludes.

2.2 Hypothesis Development

Theoretical work on liquidity regulation analyzes different types of market failures and provides a justification for such regulation. In order to develop hypothesis on the implications of liquidity requirements on borrowers, we first seek to understand how these requirements interact with capital requirements. The way they interact has consequences on whether liquidity requirements are beneficial or costly to banks, and thus on how they might affect loan contract terms. While theory work is limited in this area, we discuss two papers that address this issue. As mentioned previously, we draw conflicting predictions from these papers.

Calomiris, Heider, and Hoerova (2015) suggest that capital and liquidity requirements are substitutes. Although the motivation for capital requirements is to limit default risk while that for liquidity requirements is to limit liquidity risk, the authors argue that both of these requirements can affect both of these types of risks. In their model, not only does cash help reduce liquidity risk, it also helps reduce default risk. Because cash is both riskless and observable, they argue that cash holdings have important implications for a bank's incentives on risk management decisions, and investors are more willing to provide funding to banks with high cash holdings. Moreover, in their model, the default risk mitigation implications of cash are more important than liquidity risk mitigation implications. This suggests that liquidity and capital requirements could act as substitutes, in which case it is likely that liquidity requirements will impose extra costs on banks. Requiring banks to hold extra liquid assets could then mean they are losing returns that could have been earned had the money been invested elsewhere. In this case, it is possible that these costs get passed down to borrowers as unfavorable lending terms.

On the other hand, the results of Acharya, Mehran, and Thakor (2015) suggest that capital and liquidity requirements are complements. Their model considers two types of moral hazard – manager shirking in monitoring responsibilities, and risk shifting by bank shareholders. In their model, debt holders provide monitoring incentives by threatening to liquidate a bank if the manager does not monitor loans. The authors argue that while capital requirements help solve risk-shifting moral hazard issue, they make debt so safe that creditors lose the incentives to discipline and encourage banks to monitor loans. Therefore, they suggest that banks should maintain a "special capital account" (SCA), which can only be invested in safe assets, and in case of insolvency, does not accrue to credit holders. This special account is akin to liquidity requirements. The authors argue that this arrangement makes sure that creditors have enough skin in the game to engage in disciplining the manager to monitor loans.

If liquidity and capital requirements are complementary as implied above, a combination of these two requirements could help enhance the stability of a bank, and bring down funding costs for banks. This would then imply that banks will be able to offer better lending terms to borrowers.

Given conflicting theoretical predictions, how LCR rule affects loan contract terms is ultimately an empirical question.

2.3 The Setting

This section describes liquidity requirements, and provides a timeline for their implementation in the U.S. It also provides a description for capital requirements to provide the reader an overview of other events happening around the same time the liquidity requirements were introduced.

2.3.1 Liquidity Requirements

In December 2010, the Basel committee introduced new liquidity requirements, as part of the Basel III accord.[50] These requirements include *Liquidity Coverage Ratio* (LCR) and *Net Stable Funding Ratio* (NSFR). While the NSFR rule requires a bank to hold enough liabilities that are expected to remain stable for at least a year, the LCR rule

[50] See House, Sablik, and Walter (2017), Bouwman (2013), Polk (2013) for details on the requirements.

requires banking organizations to hold enough high quality liquid assets (HQLA) to cover expected net cash flow during a 30-day standardized stress scenario. In the U.S., the financial regulators – the Federal Reserve, the Office of the Comptroller of the Currency (OCC), and the Federal Deposit Insurance Corporation (FDIC) – issued a final version of LCR in September 2014.[51]

The LCR rule requires that the ratio of HQLA to total net cash outflows be 100%, and that banks maintain this ratio on an ongoing basis. The rule specifies three different groups of assets that can be counted as HQLA: level 1, level 2A, and level 2B. Level 1 assets are the most liquid of these and level 2B are the least liquid.[52] While the values of level 1 assets count 1-1 towards the computation of the liquidity coverage ratio, other levels are subject to haircuts and limits on how much they can account towards the total stock of HQLA.[53] In regards to the denominator of LCR, the rule specifies standardized assumptions on rates of cash inflow and outflow in a stress scenario, and these rates depend on the types of instruments that the bank holds.[54]

In the U.S., the LCR rule applies differently to different banks depending on their size. Advanced approaches banking institutions – those with $250 billion or more in total assets, or $10 billion or more in on-balance sheet foreign exposure – are subject to 'full' LCR. Also subject to this rule are their subsidiaries that are depository institutions with $10 billion or more in total consolidated assets. These institutions had to meet 80% of their LCR requirements in 2015, 90% in 2016, and were fully compliant by 2017.

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[51] At the time of this writing, the regulators in the U.S were inviting comments on the proposal for rules on NSFR that was issued in April 2016.

[52] Level 1 assets include things like Federal Reserve balances, reserves held at foreign central banks, treasury securities, securities issued by U.S. government agencies, low risk securities issued by foreign sovereign entities etc. Level 2A assets include securities issued by U.S. government sponsored entities such as Fannie Mae, and Freddie Mac, high risk securities issued by foreign sovereign entities etc. Level 2B include liquid corporate debt securities and common stocks meeting certain criteria (see House, Sablik, and Walter (2016)).

[53] Level 2A assets are discounted at 15% in the computation of HQLA and they cannot make up more than 40% of the organization's total HQLA. Level 2B assets are discounted at 50% and they are capped at 15%.

[54] See Polk (2013) for details on these inflow/outflow rates. Cash inflows are also capped at 75% of cash outflows, such that the HQLA accounts for at least 25% of the total expected cash outflows.

Banking institutions having total assets between $50 billion and $250 billion are subject to ‘modified’ LCR. These institutions were 90% compliant in 2016 and were fully compliant by 2017. These institutions have less stringent requirements compared to those that are subject to full LCR rule.

2.3.2 Capital Requirements

In addition to liquidity requirements, Basel III introduced higher capital standards. These capital requirements went into effect a year prior to the liquidity requirements. While only banks that have asset size greater than or equal to $50 billion are subject to liquidity requirements, banks of all sizes are subject to higher capital standards, with the largest banks facing the most stringent rules.

Basel III increases the minimum required level of Tier 1 capital ratio (Tier 1 capital to risk-weighted asset ratio) from 4% to 6%.[55] For advanced approaches banks, compliance for this rule began in 2014 and was phased in gradually to 6% in 2015.[56] The rest of the banks had to comply beginning 2015. Basel III, however, keeps the total capital requirement (Tier 1 plus Tier 2 capital ratio) fixed at 8%.

Beginning 2016, all banking organizations are also subject to an additional Tier 1 capital requirement of 2.5%, also known as *capital conservation buffer,* which effectively brings up the minimum Tier 1 capital requirement to 8.5% and total capital requirement to 10.5%. Moreover, advanced approaches banks are subject to a new countercyclical capital buffer requirement, ranging between 0 - 2.5% at regulator’s discretion. At the time of this writing, this buffer requirement was set at 0%. These advanced approaches banks will also be subject to a new supplementary leverage ratio (Tier 1 capital to total leverage

[55] See Ennis and Price (2011), Polk (2013) for details on Basel III capital requirements.
[56] For advanced approached banks, the minimum requirement on Tier 1 ratio was 5.5% in 2014 and 6% in 2015.

exposure) requirement beginning 2018.[57] Figure 1 summarizes the timeline of compliance dates for all of these events for advanced and non-advanced banks separately.

2.4 Methods

2.4.1 Model

In order to estimate the effect of LCR, we compare the changes in contract terms on loans issued by treated banks around the time of LCR, with those on loans issued by control banks. There are two events in our setting – one in Jan 2015 and another in Jan 2016. We follow the method in Gormley and Matsa (2011) to analyze such setting of multiple events. In particular, for each event, we create a cohort of treated and control banks using observations for loans they issue from 2013 to 2016. For the 2015 cohort, if a control bank gets treated by the latter event, we drop those post-observations. We then create a similar cohort of observations for the 2016 event. Finally, we stack both of these samples to create one dataset, and estimate the following model:

$$\begin{aligned} Y_{i,c,t} = \alpha_{t,c} + \alpha_{i,c} + \beta_1 LCR_{i,c,t} &+ borrower\ controls + lender\ controls \\ &+ loan\ characteristics + loan\ type\ F.E \\ &+ borrowerSIC\ F.E \end{aligned} \tag{8}$$

where $Y_{i,c,t}$ is one of the loan contract terms (discussed in the next section) on new loans issued by bank *i* in cohort *c* at time *t* . $LCR_{i,c,t}$ indicates whether lender *i* is treated by time *t*. This variable is the difference-in-difference term or the interaction between the dummy variable that identifies a treated bank and the dummy variable that indicates the post period. $\alpha_{t,c}$ and $\alpha_{i,c}$ are time-cohort and lender-cohort fixed effects respectively. We control for several other borrower, lender, and loan characteristics as described in the

[57] Total leverage exposure is the unweighted total assets constituting both on-balance sheet and off-balance sheet items.

next section. Furthermore, we include loan type and borrower industry (four-digit SIC) fixed effects.

The observations in our dataset are potentially correlated with one another. First, several of the loans in our sample are issued by the same lender and some of these lenders could belong to the same bank holding company, such that common lender characteristics introduce correlations amongst these observations. Second, several of these loans could be issued to the same borrower, such that common borrower characteristics introduce correlations amongst observations. And third, the same loan can appear more than once in our dataset because of the way we stack samples for each event to form one dataset. Furthermore, if a loan has multiple lead arrangers, we keep observations for the loan for each lead arranger. We account for these issues by double clustering standard errors at the bank holding company and borrowing company levels. For independent banks, we double cluster standard errors at the lending bank and borrowing company levels.

One advantage of the regression framework in equation (8) is that it accounts for the fact that the LCR rule went into effect in two stages, such that we can use all banks that were not subject to this rule as control banks, even though they are treated later in the sample period. This way, our control group is not limited to those that are not subject to LCR at all, and this method can be used even if all banks are eventually subject to treatment (Gormley and Matsa (2011)). Additionally, this setting of multiple events is helpful in showing that our results are robust to multiple events, and that the results are not being driven by only one set of treated banks.

2.4.2 Confounding Events

In the regression framework in equation (8), the use of control banks serves to control for any other events happening simultaneously with LCR that affect both treated and control banks. For example, Bank of America, which is an advanced approaches bank, was subject to "full LCR" rule in 2015. Changes in contract terms on loans issued by this bank around LCR could be driven by other things happening in 2015 such as the economic conditions of the year. By comparing these changes with changes in contract terms in loans issued by a control bank, which is also subject to the same economic conditions, we filter out the effect of the economic conditions in our estimates.

Another possible confounding event is the implementation of higher standards for capital requirements, however given the fact that these requirements went into effect a year prior to liquidity requirements, we are able to identify the effect of LCR. For advanced approaches banks, the new capital requirements went into effect in the beginning of 2014, while for non-advanced approaches banks, these capital requirements went into effect in the beginning of 2015. Therefore, by the time LCR first went into effect in Jan 2015, all banks were already subject to the new capital requirements, such that comparing the treated bank's changes in loan contract terms with that of the control bank's loan contract terms filters out the effect of capital requirements.

For example, because Bank of America is an advanced approaches bank, it was subject to new capital requirements in 2014 and to LCR in 2015. To account for changes in loan contract terms due to capital requirements, we compare Bank of America's loans in the year 2015 with Suntrust bank's loans in the same year. Suntrust bank is a non-advanced approaches bank that was not subject to LCR until 2016 but was already subject to capital requirements in 2015 (see Figure 1). By doing so, we compare changes in contract terms in loans from two banks that are both subject to capital requirements, but only one of them is subject to LCR.

Similarly, for banks with asset size between \$50 billion and \$250 billion, which had to comply with the modified LCR rule in 2016, any bank below \$50 billion in asset size serves as a control bank. Banks below \$50 billion in size are not subject to LCR, but were required to comply with higher capital requirements beginning 2015. These banks also serve as control banks for the advanced approaches banks. Also, as Figure 1 indicates, banks were subject to capital conservation buffer requirement the same year modified LCR went into effect. Again, since all size banks were subject to this requirement, using banks below $50 billion in size as control for banks treated in 2016 event should control for this event.[58]

2.4.3 Manipulation of Size

In order to identify the effect of LCR, the difference-in-difference method assumes that banks did not manipulate their size to avoid compliance with this rule. If they did, the OLS regression estimates will be biased. Figure 2 plots the size (total assets in billions of dollars) distribution of banks in the sample. Panel A presents the distribution for September 2013, while panel B presents that for September 2014. Banks meeting asset thresholds as of September 2014 were required to comply with LCR. Comparing the two plots, we do not observe any significant changes in the distribution of size around the cut-off points for $50 and $250 billion. If anything, banks appear to have grown in size, and there is no evidence that they cut down size to avoid compliance.

2.5 Data and Variables

2.5.1 Data and Sample

For this study, we use three sources of data – Dealscan for data on loan issuances, Compustat for borrowing company financial information and the call report database for bank balance sheet information.

We begin with loan level data from Loan Pricing Corporation's (LPC) Dealscan database (obtained from Wharton Research Data Services (WRDS)). This database consists primarily of syndicated loans that are issued by both banks and non-banks since

[58] During the sample period, no bank was subject to countercyclical capital buffer requirement. The Federal Reserve issued its final policy statement on this requirement only in September 2016, and it voted to keep this buffer at 0% in October 2016.
(See https://www.federalreserve.gov/newsevents/pressreleases/bcreg20161024a.htm.)

1981. It provides information on name and location of borrowers and all lenders in the syndicate, the amount, type, purpose, maturity, and origination date of the loan, and information on loan pricing and contract terms.[59] According to LPC, majority of the data (70%) comes from SEC filings, and the rest comes from direct research with contacts at banks. For this paper, we obtain a subsample of U.S dollar denominated loans that have no missing loan pricing/maturity information and that were originated between 2013 and September 2016 (date when we extracted data for this study). We choose this time period to ensure that we have at least two years of loan origination data prior to implementation of the LCR rule.

The basic unit of observation in Dealscan and in this paper is a loan/facility. Multiple facilities to a borrower are grouped into deals/packages. A syndicate of lenders originates loans in each package, and Dealscan provides information on the role of each of these lenders. We focus only on lead lenders since they hold a greater share of a loan, and they are typically responsible for making loan decisions and setting contract terms (Berger, Roman, and Makaew (2015)). We largely follow Berger, Roman, and Makaew (2015) and Ivashina (2009) in identifying lead lenders. If a lender is marked as “administrative agent” or “sole lender,” we identify it as a lead lender. If we cannot identify a lead lender this way, we mark any lender identified as “Agent," "Arranger," "Bookrunner," "Lead arranger," "Lead manager," or "Mandated Lead arranger” as lead. We only keep facilities for which we are able to identify a lead lender, and in case of multiple lenders, we keep observations corresponding to all of them. In this sample, a lead lender holds, on average, 14.28% of loan share.

We then match the lenders in our sample with call report database using lender name, location, and dates of operation.[60] All financial institutions regulated by the Federal Reserve System, Federal Deposit Insurance Corporation (FDIC), and the Comptroller of Currency are required to file the Report of Condition and Income or call reports on a quarterly basis. These reports provide detailed information on a bank’s income statement,

[59] See Carey, Post, and Sharpe (1998), Chava and Roberts (2008) for description of the Dealscan database.

[60] We thank Vance Anthony for providing us with a SAS program that matches names.

balance-sheet items and off-balance-sheet activities, and are publicly available through Federal Reserve Bank of Chicago (we obtain it from WRDS). If we are unable to find a match, we match the lender to their bank holding company. For each lender, we obtain financial information from call reports as of the quarter immediately prior to facility start date.

Finally, we match borrowers in our sample with compustat using borrower company name, and use this database to obtain borrower financial information. If a match is not available, we match the borrower to parent company using FactSet database. For each borrower, we obtain financial information from compustat as of the fiscal quarter immediately before the facility start date.

After obtaining data from the above sources, our final sample (not stacked) has a total of 50 unique banks with 4377 loan observations. Of the 50 banks, 18 were treated in 2015, 24 were treated in 2016, and the rest were not treated at all.

2.5.2 Variables

Following Berger, Roman, and Makaew (2015), we study five different loan contract terms: loan size, spread, maturity, collateral, and covenant intensity index. *Log(Loan Size)* is the natural logarithm of the dollar amount of loan reported in Dealscan. *Spread* is all-in-spread (drawn) in percent. All-in-spread is the interest that the borrower pays in basis points over LIBOR for each dollar drawn. This amount is inclusive of any other fees charged by the lenders. *Log(Loan Maturity)* is the natural logarithm of loan maturity reported in months. Next, Dealscan reports a Yes/No variable identifying whether a loan is collateralized. We construct a dummy variable *Collateral* that identifies the presence of collateral.[61]

[61] If information on collateral is missing, we assume that the loan does not require collateral. Similar results obtain if we delete all observations that have missing values for collateral.

Finally, we construct *CovIndex*, the covenant intensity index of Bradley and Roberts (2015). Following their paper, we first construct six dummy variables that indicate whether the loan contains dividend restriction, asset sales sweep, equity issuance sweep, debt issuance sweep, collateral, and more than two financial covenants.[62] These covenants impose penalties on the borrower conditional on violation of the specified terms. The covenant intensity index is just the sum of these six dummy variables, so this variable takes a value between 0 and 6. Higher values of this index indicate greater restrictions on borrower activities.

We include several control variables in our regressions. First, we include control variables for bank characteristics. These include lender size as measured by the natural logarithm of total deposits (expressed in 2014 dollars), capital-to-asset ratio (total equity/GTA where GTA or gross total assets is the sum of total assets plus allowance for loan and lease losses plus the allocated transfer risk reserve), management quality (overhead costs/GTA), return on assets (ratio of interest income to GTA), and fee income share (non-interest income/GTA).

Second, we include controls for borrower characteristics. These include borrower size as measured by the natural logarithm of total assets (expressed in 2014 dollars), borrower market to book ratio (ratio of market to book value of the borrower equity), leverage (long-term debt to assets ratio), profitability (operating income before depreciation to asset ratio), and cash holdings ratio (cash and short-term investments to assets ratio). To account for credit risk of borrowers, we use S&P ratings for each borrower. Following Hollander and Verriest (2016), we construct a variable that encodes ratings with numeric values, such that higher values are assigned to higher rating notches. If rating information is unavailable, this variable takes the value 0. We also interact this variable with a dummy variable that takes the value 0 if rating information is unavailable.

Finally, we include control variables for loan characteristics. These include loan spread, size, and maturity. To ensure that our results are not influenced by outliers, we

[62] For loan observations that have missing covenant information in Dealscan, we assume that the covenant is not included in that loan.

winsorize all dependent and independent variables at 1%. Summary statistics appear in Table 2.1. These statistics are based on unstacked sample to avoid any double counting.

2.6 Empirical Results

2.6.1 Loan Contract Terms

Table 2.2 presents regression results for how LCR affects loan contract terms. Columns (1) through (5) present results for spread, loan size, maturity, presence of collateral, and covenant intensity index respectively. Here, the term *LCR* is the variable of interest which takes the value 1 for treated banks post LCR implementation.

The first three columns do not show any statistically significant impact on spread, size, or maturity of a loan issued by treated banks after LCR went into effect. Similarly, the impact on covenant index is also not significant. However, the probability that collateral is required increases, and this result is also economically significant. For example, the probability that collateral is required in new loans issued post LCR increases by 16.7%.

These results indicate some signs of increased cost for borrowers following LCR. Since banks are required to set aside liquid assets that could have been invested elsewhere, it is sensible that they are prompted to implement stronger collateral requirements to ensure that borrower activities are monitored well and that borrowers do not default on their obligations. That there is no effect on pricing terms suggests that this requirement did not impose high costs on the part of lenders to price them, although it incentivized banks to take steps to make investments safer.

2.6.2 Liquidity Ratio and Contract Terms

We further investigate possible costs imposed by LCR on banks by comparing groups of banks that are expected to find it more costly ex-ante with those that are not expected to find it as costly. Intuitively, if the implementation of LCR was costly, we expect the costs to be more visible for banks with low ex-ante liquidity ratio, and expect them to pass it down to borrowers. We define liquidity ratio as the ratio of cash to total deposits (Duchin and Sosyura (2014)). Since the asset size of a bank as of September 2014 determines whether a bank is subject to LCR or not, we obtain liquidity ratio of banks as of this date. A bank has high liquidity ratio if the ratio is greater than or equal to the median for the sample, and it has low liquidity ratio if the ratio is below the median.

Table 2.3 presents results for this test. Panel A presents results for banks with high ex-ante liquidity ratio. Panel B presents results for those with low ex-ante liquidity ratio. The results in Panel A show that banks with high liquidity enjoy benefits arising from LCR as they offer lower spread and longer maturity on new loan issues to borrowers. This is supportive of the hypothesis that the implementation of LCR decreases funding costs, likely because investors view banks as being safer with high liquid holdings. However, the probability that a loan requires collateral increases and the count of covenants included on new loan issues increases as well. This indicates that while banks do pass down cost savings to borrowers, they also take steps to insure themselves against losses by improving monitoring of borrower activities.

These results are economically significant as well. For example, compared to control banks, a treated bank post implementation of LCR decreases spread on new loan issues by 80.5 basis points, which is large compared to a mean of 195 basis points for the sample. Such a bank also increases the maturity of a new loan by 12.7%. However, the probability that a new loan issue requires collateral increases by 29.8% and these loans require 1.29 additional covenants.

Panel B presents results for banks with low ex-ante liquidity ratio. While results show that these banks decrease the amount of loans that they extend to borrowers, there is no evidence of unfavorable terms in any other dimension of loan contract. Specifically, the second column shows that banks having low liquidity ratio decrease loan size by 51.4%, indicating that these banks take steps to reduce their risk exposure.

That there is no change is pricing terms by banks with low ex-ante liquidity ratio could be indicative of either modest costs of LCR or lack of pricing power (due to competition, for example). However, given that lenders with high ex-ante liquidity ratio offer lower pricing terms to borrowers, we interpret these two results together to be indicative of modest costs of LCR to lenders. Banks do take steps to hedge against losses by increasing collateral/covenant requirements and by reducing loan exposure. While we do not study how costly additional covenants are to the borrowers, it is interesting that borrowers do not find an increase in loan prices post LCR.

2.6.3 Relationship Strength and Contract Terms

In this section, we investigate if treated banks change loan contract terms differently for borrowers with varying relationship strength. The literature suggests both costs and benefits to borrowers from relationship lending, and we investigate whether such relationship determines if a borrower faces favorable or unfavorable contract terms post LCR.

Boot (2000) provides an overview of the literature in the area of relationship lending, and notes that in such lending, banks collect proprietary information on the borrower through multiple interactions. This information is reusable in the future due to which both parties mutually benefit from improved exchange of information. However, the author also points out a possible hold-up cost to borrowers. A hold-up problem arises due to information monopoly that banks enjoy by collecting borrower information over the course of the lending relationship. For a borrower, there are costs to breaking current relationship and starting a new one with a different bank. This may allow banks to take advantage of the proprietary information they generate to extract non-competitive rents from borrowers.

We follow Bharath et al. (2011) in defining relationship strength for a given pair of bank and borrower. For this, we study all lending relationships during the 5 year period preceding the facility start date. The strength of the relationship between borrower *i* and lender *j* is the ratio of the total value of loans received by borrower *i* from lender *j* in the five year period to the total value of loans taken out by borrower *i.* Any bank-borrower pair having relationship strength greater than or equal to the median for the sample in a given year is labeled as high strength and any such relationship below the median is labeled low.

Table 2.3 includes an interaction term between LCR and the variable identifying high relationship strength with the borrower. Results show that while borrowers with high relationship strength used to enjoy lower spreads compared to borrowers with low relationship strength prior to LCR, treated banks increase spread on loan issues to high relationship borrowers post LCR such that there is now no benefit to relationship, i.e., there is no net difference in pricing terms for high versus low relationship borrowers post LCR.

Specifically, prior to the implementation of LCR, banks were charging 12.8 basis points lower to high relationship borrowers compared to low relationship borrowers. After the introduction of the LCR rule, banks charge 18.2 basis points more to relationship borrowers, thus implying that banks are no longer provide relationship benefits to borrowers as they used to. On the other hand, there is no impact on spread to low relationship strength borrowers post LCR. However, banks do decrease their risk exposure by increasing collateral requirement for them. Specifically, post LCR, the probability that collateral is required for loans to low relationship strength borrowers increases by 16.4%. That there are no changes in other dimensions of loan contract terms for high relationship borrowers indicates that banks likely have enough good information on these borrowers from their past relationships such that there is no need to reduce risk exposure to them.

Overall, results indicate that relationship borrowers no longer enjoy benefits arising from their past relationships after the implementation of the LCR rule. For borrowers having low relationship strength, there are no changes in pricing terms. While banks do not provide extra benefits to relationship borrowers in the form of lower spreads as before, we interpret both of these results combined to be indicative be little costs of the LCR rule to borrowers. Consistent with prior results, banks do however insure themselves against potential defaults by increasing collateral requirements for low relationship borrowers for whom banks do not hold as much prior information to gauge at their likelihood to make future payments.

2.6.4 Placebo Test

In this subsection, we conduct a placebo test. In particular, for this test, we assume that the LCR went into effect a year prior to the actual year of implementation. If the results on loan contract terms that we observed in prior subsections were due to the implementation of LCR and not due to any other confounding events, we expect there to be no results visible in this falsification test.

Table 2.6 presents the results for the false event. Specifically, the variable *LCR* takes the value 1 for treated banks post the false LCR event. As table 2.6 shows, there is no evidence of an impact of this false event on any of the loan contract terms. This lends support to the argument that prior results on increased presence of collateral on loans are attributable to the implementation of LCR.

2.7 Conclusion

In this paper, we study the implications of one of the new liquidity requirements – the Liquidity Coverage Ratio (LCR) rule – on loan contract terms. Studying the impact on contract terms of new loans issued after LCR allows us to study whether the requirement was costly for banks and how it changes their behavior. Since an impact on loan contract terms has potential impact on the financial condition of borrowers, this study also sheds some light on the real effects of the rule.

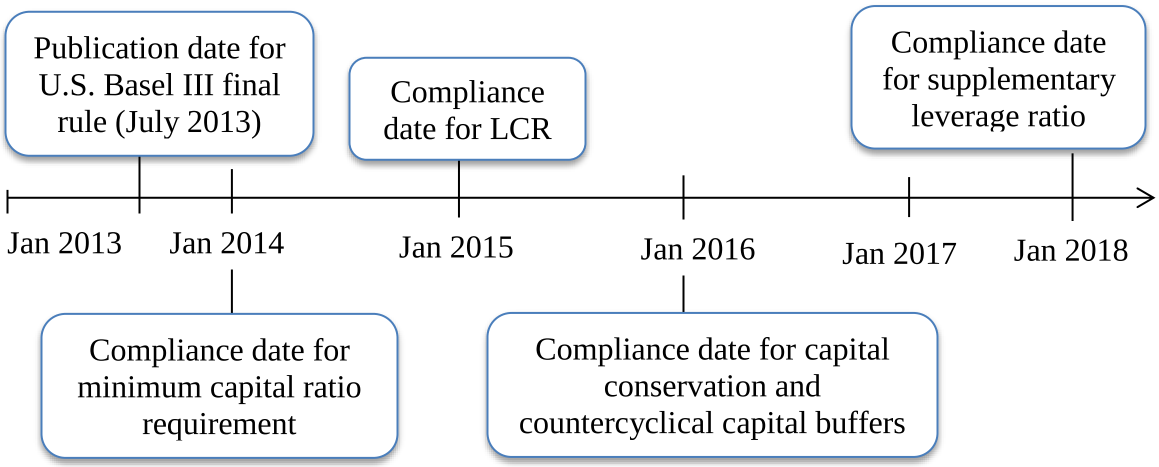
Results indicate that LCR imposes modest costs on banks since there is no evidence of increased pricing terms on a loan. Since banks are setting aside liquid assets that could have earned return elsewhere, they take steps to insure themselves against default losses by requiring higher collateral requirements. Comparison of banks with high versus low liquidity ratio corroborates this finding of limited costs of LCR on banks. Banks with high liquidity ratio ex-ante, which are expected to experience the least cost from LCR, offer more favorable pricing terms, however they do strengthen monitoring by requiring collateral and more number of covenants. On the other hand, banks with low liquidity ratio that are expected to find LCR comparatively costlier, do not change any of the loan pricing terms.

Further results suggest banks no longer provide extra benefits to relationship borrowers in the form of lower price spreads as they used to prior to the implementation of the LCR rule. However, there is no change in pricing terms to borrowers with low relationship strength, which is again evidence of limited costs of the LCR rule to banks. As before, banks do reduce risk exposure to borrowers with low relationship banks by requiring higher collateral.

Figure 2.1: Basel III Compliance Timeline

This figure presents compliance timeline for capital and liquidity requirements of the Basel III accord. Panel A presents timeline for advanced approaches banks, while panel B presents that for non-advanced approaches banks. An advanced approaches bank is any banking organization with $250 billion or more in total consolidated assets, or $10 billion or more in on-balance sheet foreign exposure.

Panel A: Advanced approaches banks



Panel B: Non-advanced approaches banks

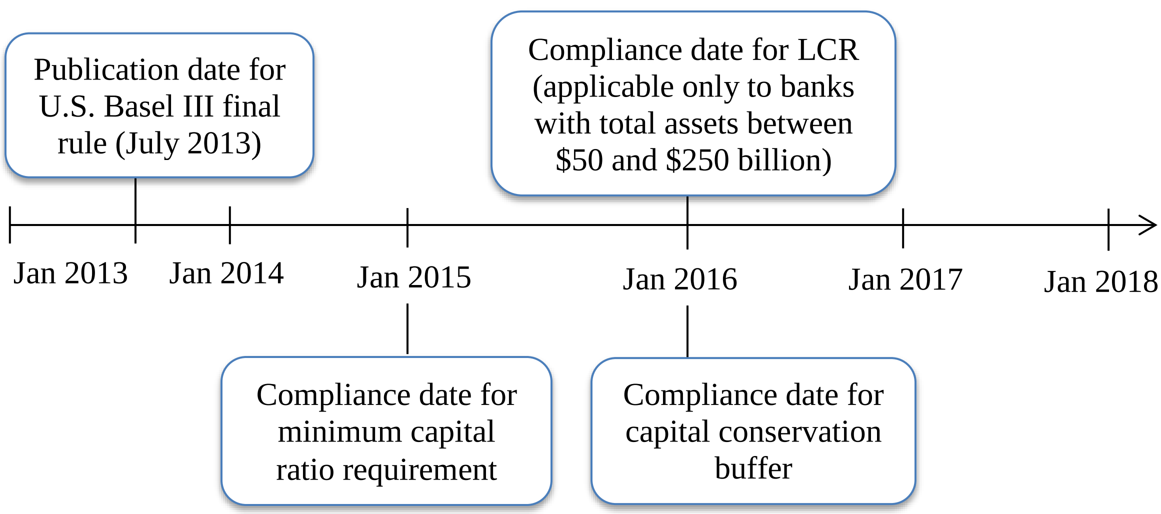
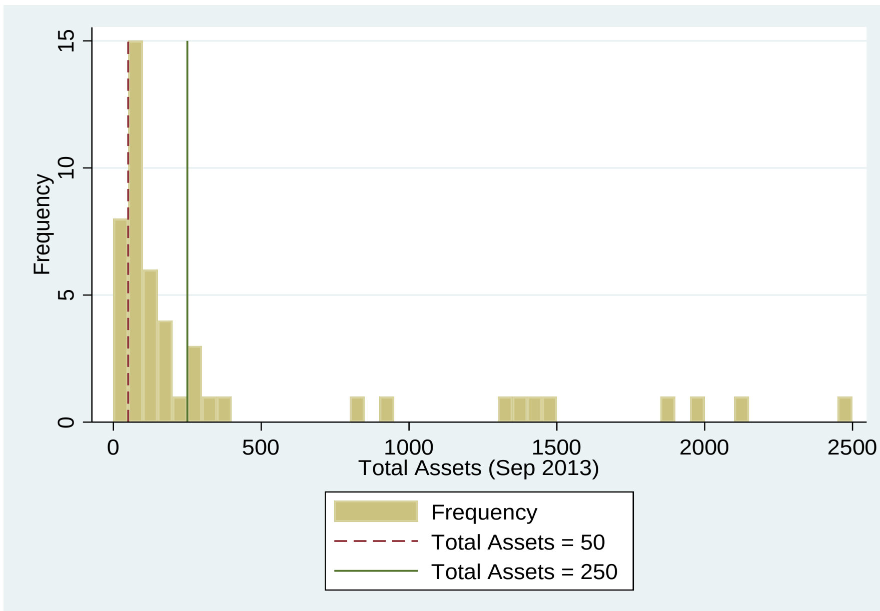


Figure 2.2: Size Distribution

This figure presents the size distribution of the sample at different points in time. Size is measured using total assets expressed in billions of dollars. Bin size used for the histogram is 50. Panel A presents the distribution as of September 2013, while Panel B presents the distribution as of September 2014. Banks meeting asset thresholds as of September 2014 are required to comply with liquidity requirements.

Panel A



Panel B

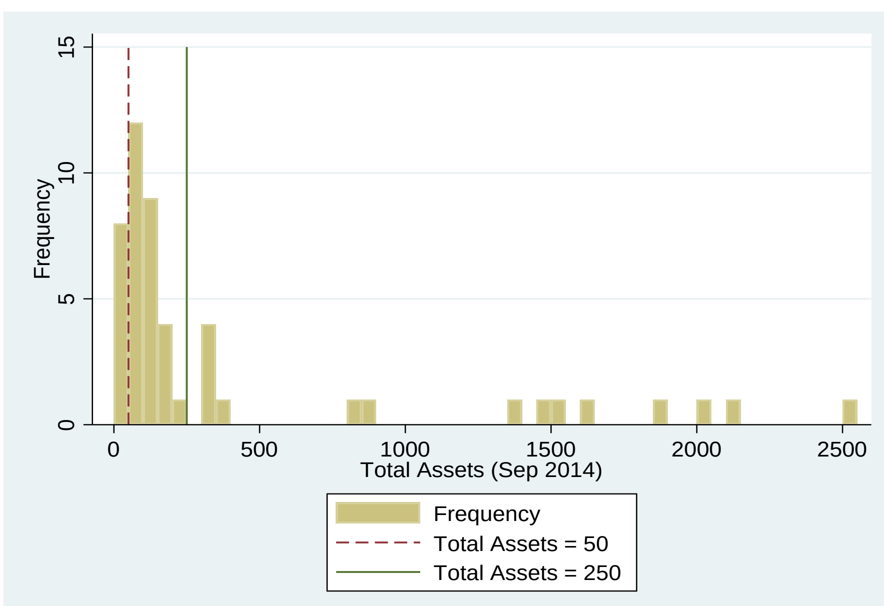


Table 2.1: Summary Statistics

This table presents summary statistics for all variables used in the regressions. *Spread* is all-in-spread expressed in percent, *Loan Size* is the natural logarithm of the amount of loan, *Maturity* is the natural logarithm of loan maturity expressed in months, *Collateral* indicates the presence of collateral, while *Covenant Intensity Index* is the count of different covenants included in the loan (six different covenants are considered as explained in the text). *Log(lender size)* is the natural logarithm of total deposits (expressed in 2014 dollars), *Lender CAR* (capital asset ratio) is total equity to GTA (GTA or gross total assets is the sum of total assets plus allowance for loan and lease losses plus the allocated transfer risk reserve), *Lender MGMT (management) quality* is overhead costs/GTA, *Lender ROA* is ratio of interest income to GTA, and *Lender Fee Income Share* is non-interest income/GTA. *Log(borrower size*) is the natural logarithm of borrower total assets (expressed in 2014 dollars), *Borrower Market-to-Book* ratio is the ratio of market to book value of the borrower equity, *Borrower Leverage* is long-term debt to assets ratio, *Borrower Profitability* is operating income before depreciation to asset ratio, and *Borrower Cash Holdings Ratio* is cash and short-term investments to assets ratio.

Variable	N	Mean	SD	Min	P5	Median	P95	Max
Loan Contract Terms								
Spread	4377	1.950	1.15	0.30	0.75	1.63	4.25	7.00
Loan Size	4377	19.810	1.32	16.12	17.50	19.81	21.82	22.74
Maturity	4377	53.300	18.00	1	12.00	60	84	180
Collateral	4377	0.420	0.49	0	0.00	0	1	1
Covenant Intensity Index	4377	1.150	1.53	0	0.00	1	4	6
Lender Characteristics								
log(Lender Size)	4377	20.960	0.92	17.79	18.51	21.35	21.57	21.59
Lender CAR	4377	0.100	0.01	0.08	0.08	0.11	0.13	0.16
Lender MGMT Quality	4377	0.020	0.01	0.01	0.01	0.02	0.03	0.04
Lender ROA	4377	0.000	0.00	0.00	0.00	0.00	0.01	0.01
Lender Fee Income Ratio	4377	0.450	0.10	0.21	0.32	0.46	0.68	0.83
Borrower Characteristics								
log(Borrower Size)	4377	8.190	1.69	4.63	5.51	8.11	11.06	12.65
Borrower Market-to-Book	4377	3.390	5.85	-15.73	0.30	2.34	10.09	40.86
Borrower Leverage	4377	0.280	0.20	0.00	0.00	0.26	0.65	0.93
Borrower Profitability	4377	0.030	0.02	-0.02	0.00	0.03	0.07	0.11
Borrower Cash Holdings Ratio	4377	0.100	0.11	0.00	0.00	0.06	0.32	0.54

Table 2.2: Loan Contract Terms

This table studies how treated banks change loan contract terms after the implementation of *Liquidity Coverage Ratio* (*LCR)* requirement. Columns (1) – (5) report OLS regression estimates for equation (8), in which the dependent variable used is *Spread*, *Loan Size*, *Maturity*, *Collateral*, or *Covenant Intensity Index* respectively. These variables are computed as described in the text (or see table 2.1). The main independent variable is *LCR*, which takes the value 1 for a treated bank post LCR. The sample period is between 2013 and September 2016. All regressions include bank, borrower, and loan controls (see table 2.1 for definition). Also included are year-cohort, bank-cohort, loan type, and 4-digit SIC industry fixed effects. Standard errors are double clustered at bank holding company (lending bank for independent banks) and borrower levels, and are reported in parenthesis. Finally, *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	(1)	(2)	(3)	(4)	(5)
	Spread	Loan Size	Maturity	Collateral	Covenant Index
LCR	-0.07	-0.128	0.047	0.167***	0.399
	(0.152)	(0.089)	(0.039)	(0.054)	(0.243)
Bank Control Variables	Y	Y	Y	Y	Y
Borrower Control Variables	Y	Y	Y	Y	Y
Loan Characteristics	Y	Y	Y	Y	Y
Year-Cohort F.E	Y	Y	Y	Y	Y
Bank-Cohort F.E	Y	Y	Y	Y	Y
Loan Type F.E	Y	Y	Y	Y	Y
Borrower Industry F.E	Y	Y	Y	Y	Y
Observations	7014	7014	7014	7014	7014
Adjusted Within R-squared	0.222	0.375	0.052	0.186	0.103

Table 2.3: Liquidity Ratio and Loan Contract Terms

This table presents changes in loan contract terms around LCR for banks with high liquidity ratio (Panel A) and for banks with low liquidity ratio (Panel B). Banks with high (low) liquidity ratio are the ones that have liquidity ratio (cash to deposits ratio measured as of September 2014) greater than or equal to (less than) the median for the sample. Columns (1) – (5) report OLS regression estimates for equation (8), in which the dependent variable used is *Spread, Loan Size, Maturity, Collateral,* or *Covenant Intensity Index* respectively. These variables are computed as described in the text (or see table 2.1). The main independent variable is *LCR*, which takes the value 1 for treated banks post LCR. The sample period is between 2013 and September 2016. All regressions include bank, borrower, and loan controls (see table 2.1 for definition). Also included are year-cohort, bank-cohort, loan type, and 4-digit SIC industry fixed effects. Standard errors are double clustered at bank holding company (lending bank for independent banks) and borrower levels, and are reported in parenthesis. Finally, *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

Panel A

	(1)	(2)	(3)	(4)	(5)
	Spread	Loan Size	Maturity	Collateral	Covenant Index
LCR	-0.805**	0.192	0.127**	0.298***	1.290***
	(0.370)	(0.194)	(0.047)	(0.063)	(0.391)
Bank Control Variables	Y	Y	Y	Y	Y
Borrower Control Variables	Y	Y	Y	Y	Y
Loan Characteristics	Y	Y	Y	Y	Y
Year-Cohort F.E	Y	Y	Y	Y	Y
Bank-Cohort F.E	Y	Y	Y	Y	Y
Loan Type F.E	Y	Y	Y	Y	Y
Borrower Industry F.E	Y	Y	Y	Y	Y
Observations	6242	6242	6242	6242	6242
Adjusted Within R-squared	0.228	0.374	0.057	0.199	0.104

Panel B

	(1) Spread	(2) Loan Size	(3) Maturity	(4) Collateral	(5) Covenant Index
LCR	-0.064	-0.415**	-0.007	0.099	-0.543
	(0.235)	(0.146)	(0.097)	(0.174)	(0.795)
Bank Control Variables	Y	Y	Y	Y	Y
Borrower Control Variables	Y	Y	Y	Y	Y
Loan Characteristics	Y	Y	Y	Y	Y
Year-Cohort F.E	Y	Y	Y	Y	Y
Bank-Cohort F.E	Y	Y	Y	Y	Y
Loan Type F.E	Y	Y	Y	Y	Y
Borrower Industry F.E	Y	Y	Y	Y	Y
Observations	759	759	759	759	759
Adjusted Within R-squared	0.238	0.299	0.106	0.146	0.114

Table 2.4: Relationship Strength and Loan Contract Terms

This table studies whether the strength of the relationship with the borrower affects how banks change loan contract terms post LCR. Relationship strength of a given borrower with a given bank is computed as the fraction of total loans in the 5-year period preceding the facility start date that the borrower obtains from the same bank. Bank-borrower pairs with high (low) relationship strength are the ones that have the relationship strength measure greater than or equal to (less than) the median for the sample in the given year. Columns (1) – (5) report OLS regression estimates for equation (8), in which the dependent variable is *Spread*, *Loan Size*, *Maturity*, *Collateral*, or *Covenant Intensity Index* respectively. These variables are computed as described in the text (or see table 2.1). The main independent variable is *LCR,* which takes the value 1 for treated banks post LCR. The sample period is between 2013 and September 2016. All regressions include bank, borrower, and loan controls (see table 2.1 for definition). Also included are year-cohort, bank-cohort, loan type, and 4-digit SIC industry fixed effects. Standard errors are double clustered at bank holding company (lending bank for independent banks) and borrower levels, and are reported in parenthesis. Finally, *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	(1)	(2)	(3)	(4)	(5)
	Spread	Loan Size	Maturity	Collateral	Covenant Index
LCR	-0.156	-0.138	0.035	0.164***	0.36
	(0.160)	(0.094)	(0.037)	(0.054)	(0.247)
High Relationship Strength	-0.128**	0.006	0.015	-0.021	-0.046
	(0.055)	(0.052)	(0.014)	(0.024)	(0.076)
LCR * High Relationship Strength	0.182**	0.021	0.023	0.008	0.081
	(0.067)	(0.072)	(0.017)	(0.030)	(0.065)
Bank Control Variables	Y	Y	Y	Y	Y
Borrower Control Variables	Y	Y	Y	Y	Y
Loan Characteristics	Y	Y	Y	Y	Y
Year-Cohort F.E	Y	Y	Y	Y	Y
Bank-Cohort F.E	Y	Y	Y	Y	Y
Loan Type F.E	Y	Y	Y	Y	Y
Borrower Industry F.E	Y	Y	Y	Y	Y
Observations	7014	7014	7014	7014	7014
Adjusted Within R-squared	0.225	0.375	0.052	0.186	0.103

Table 2.5: Placebo Test

This table conducts a placebo test by using a false LCR event a year prior to the actual implementation date, and studies how treated banks change loan contract terms around this year. Columns (1) – (5) report OLS regression estimates for equation (8), in which the dependent variable used is *Spread*, *Loan Size*, *Maturity*, *Collateral*, or *Covenant Intensity Index* respectively. These variables are computed as described in the text (or see table 2.1). The main independent variable is *LCR*, which takes the value 1 for treated banks post false LCR event. The sample period is between 2013 and September 2016. All regressions include bank, borrower, and loan controls (see table 2.1 for definition). Also included are year-cohort, bank-cohort, loan type, and 4-digit SIC industry fixed effects. Standard errors are double clustered at bank holding company (lending bank for independent banks) and borrower levels, and are reported in parenthesis. Finally, *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	(1) Spread	(2) Loan Size	(3) Maturity	(4) Collateral	(5) Covenant Index
False LCR	0.148	-0.013	0.04	-0.013	-0.159
	(0.124)	(0.091)	(0.032)	(0.056)	(0.166)
Bank Control Variables	Y	Y	Y	Y	Y
Borrower Control Variables	Y	Y	Y	Y	Y
Loan Characteristics	Y	Y	Y	Y	Y
Year-Cohort F.E	Y	Y	Y	Y	Y
Bank-Cohort F.E	Y	Y	Y	Y	Y
Loan Type F.E	Y	Y	Y	Y	Y
Borrower Industry F.E	Y	Y	Y	Y	Y
Observations	5733	5733	5733	5733	5733
Adjusted Within R-squared	0.216	0.373	0.051	0.187	0.103

Chapter 3

Bank Liquidity Creation and Financial Stability

3.1 Introduction

According to theories of banking, a key function of banks is *qualitative asset transformation* (Bhattacharya and Thakor (1993)). This function entails two important roles that banks perform – risk transformation, and liquidity transformation or liquidity creation (Berger and Bouwman (2009)).[63] Banks create liquidity by accepting liquid deposits (e.g., transaction deposits) and originating illiquid loans (e.g., commercial loans). They also create liquidity off the balance sheet through loan commitments, letters of credit, and derivatives (e.g., credit-risk and interest-risk derivatives). Such activity allows a bank to finance projects that contribute in stimulating the real economy, and provides investors with the liquidity they seek. However, in this process, banks take liquidity risk, which means that they are subject to runs in the event of a liquidity shock (see Bryant (1980), Diamond and Dybvig (1983)).

As such, ensuring the stability of the banking system and designing policy responses during crises requires a deeper understanding of the relationship between liquidity creation and financial stability. While much of the empirical work focuses on the role of banks as risk transformers, work on banks as liquidity creators is limited (Berger and Bouwman (2009)). So, in this paper, I focus on the role of liquidity creation by banks, and ask how this activity affects the stability (inverse of default risk) of a bank.

For this study, I use a measure of liquidity creation constructed by Berger and Bouwman (2009). This is a comprehensive measure that includes both on-balance sheet

[63]Banks transform risk by accepting riskless deposits and originating risky loans (Bhattacharya and Thakor (1993)).

and off-balance sheet items. The authors classify assets, liabilities, and off-balance sheet items as liquid, semi-liquid and illiquid, and provide weights to these classes such that items that create liquidity get high weights and those that destroy liquidity get the smallest weight. The underlying idea is that liquidity is created when illiquid assets are transformed into liquid liabilities, and it is destroyed when liquid assets are transformed into illiquid liabilities. The weighted value of these items represents the total liquidity created by a bank.

Using this measure, I study how liquidity creation affects the financial stability of a bank. Following the intuition of Acharya and Naqvi (2012), who suggest that liquidity creation responds differently in different macroeconomic conditions, I compare and contrast its relationship with stability in normal times versus bad times. In particular, I conduct a study around the 2007 financial crisis, and ask how liquidity creation before the crisis affected stability during the crisis. Then, I consider a false crisis period, and conduct a similar study to draw conclusions for normal times. Furthermore, I break liquidity creation into on-balance sheet versus off-balance sheet, and asset-side versus liability-side components to study the main drivers of the relationship between liquidity creation and bank stability.

I find that overall liquidity creation is a risky activity during both normal and bad times. Much of this result is driven by off-balance sheet activity during crisis. Specifically, a standard deviation increase in off-balance sheet liquidity creation decreases the stability of a bank by 6.1%. That liquidity created off balance sheet drives the result during crisis is consistent with customers drawing down unused commitments when credit was scarce during the financial crisis. It is interesting that there is not any convincing evidence that such off-balance sheet activity offers any benefits during normal times. The negative relationship between overall liquidity creation and stability during normal times is mainly driven by on-balance sheet activity. Specifically, a standard deviation increase in on-balance sheet liquidity creation decreases the stability of a bank by 8.5%.

Breaking the on-balance sheet component further into its asset-side and liability-side shows that during the crisis, asset-side component of liquidity creation has a negative impact on stability, but liability-side has a positive impact such that the effects of the two cancel each other. This explains why on-balance sheet liquidity creation does not show a significant impact on stability. Specifically, a standard deviation increase in asset-side liquidity creation results in a 9.0% decrease in stability, while a similar increase in liability-side liquidity creation results in a 5.9% increase in stability.

One of the factors that contributed in credit contraction during the 2007 crisis was the fact that investors of wholesale funds and interest-based funds (e.g. repurchase agreements) refused to roll over funds due to concerns over solvency of banks. Given that high liability-side liquidity creation corresponds to funding through the most liquid, stable, and insured sources of funding (e.g., traditional deposits), as opposed to interest-based funding, it is sensible that banks with high liability-side liquidity creation displayed more stability during the crisis period.

On the other hand, both asset-side and liability-side components decrease stability during normal times. It is surprising that liability-side liquidity creation hurts stability during good times. A possible explanation for this is that, during normal times, investment opportunities are good, and investors are more interested in earning returns than storing them in the bank in the form of deposits that do not offer competitive rates. It helps banks to attract greater amount of funding by offering competitive interest rates in the wholesale funding market, rather than just relying on traditional deposits. So, while it makes sense for banks to rely on less liquid liabilities during normal times, this is not optimal for bad times.

Thus, these results indicate that there are both costs and benefits to liquidity production, and implications are different for different components. Further results show that during crisis, holding high amounts of liquid assets helps reduce the negative effect of off-balance sheet liquidity creation on stability, while holding high amounts of core deposits helps reduce the negative impact of on-balance sheet liquidity creation on stability. Results further show that these benefits during crisis period exceed the costs of holding such liquid assets and core deposits during normal times.

This study complements the theoretical literature that study why banks create liquidity and provide implications for riskiness of a bank (see Bouwman (2013), and

Berger, Molyneux, and Wilson (2012) for surveys in liquidity creation and relevant topics). Early work in this area include Bryant (1980) and Diamond and Dybvig (1983). Diamond and Dybvig (1983), for example, explain how banks are capable of creating more liquid deposits with smaller costs of early liquidation than are individuals holding illiquid assets directly, and why it is optimal for investors, demanding liquidity, to invest through banks. The model further shows that a bad equilibrium of bank run is possible if investors expect one another to withdraw early. Similarly, Diamond and Rajan (2001) provide explanations for why loans are illiquid, and how runs incentivize banks to commit to make payments on deposits, thereby allowing banks to create liquidity. Banks create liquidity off-balance sheet as well, and Kashyap, Rajan, and Stein (2002) suggest benefits to engaging in both on- and off-balance sheet liquidity creation. [64]

More recently, Acharya and Naqvi (2012) posit that abundant liquidity can lead to agency problems, encouraging banks to engage in excessive lending, and thus leading to asset price bubbles. This is more likely to happen when macroeconomic risks are higher, so the authors suggest that central banks should lean against liquidity and adopt contractionary monetary policies when macroeconomic risks are high.

Empirical work in this area is limited. The most relevant empirical paper is Berger and Bouwman (2010), who suggest that abnormally high liquidity creation may predict an onset of a crisis. They also study the effect of monetary policies on liquidity creation, and find an economically insignificant effect. This paper is different from theirs in that I delve deeper into the relationship between liquidity creation and stability by studying implications of the individual components of liquidity creation, and also by studying how this relationship varies in different market-wide conditions. Other papers that study loan commitments focus on customers instead and indicate that liquidity creation could help

[64] Kashyap, Rajan, and Stein (2002) argue that banks need to set aside a pool of liquid assets to meet demands of both depositors and borrowers of loan commitments. If liquidity needs of depositors and borrowers are not perfectly correlated, the same pool of liquid assets can serve liquidity needs of both customers. Furthermore, there are information advantages (lower monitoring costs) if the bank can offer other services (such as loans) to the same borrower. Also relevant is the early formalization of banks as information producers in Ramakrishnan and Thakor (1984), who also show information advantages arising from forming coalitions of information producers.

reduce credit rationing for them (e.g., Berger and Udell (1992), Ivashina and Scharfstein (2010), Campello et al. (2011)).

The rest of the paper is organized as follows. Section II describes data, model, and variables used. Section III discusses the main empirical results of the paper, and section IV concludes.

3.2 Data and Methods

3.2.1 Data and Sample

For this study, I use two main sources of data – the bank level database on liquidity creation provided by Berger and Bouwman (2009) and the call report database for bank balance sheet information.[65]

I begin with data on liquidity creation measures created by Berger and Bouwman (2009). This database provides the amount of liquidity created by US banks from 1984:Q1 to 2014:Q4. This database includes the authors' preferred "Cat fat" measure as well as other alternate measures used in their paper.[66] Since I study how liquidity creation and bank stability are related during the financial crisis and the normal period preceding the crisis, I obtain a subset of observations for the period between 2003:Q1 and 2009:Q4.

The next database I use is the call report database, which provides detailed information on a bank's income statement, balance-sheet items and off-balance-sheet activities. All financial institutions regulated by the Federal Reserve System, Federal Deposit Insurance Corporation (FDIC), and the Comptroller of Currency are required, on a quarterly basis, to file the Report of Condition and Income, also known as the Call Reports. These reports are publicly available through Federal Reserve Bank of Chicago (and can be obtained from Wharton Research Data Services (WRDS)). After obtaining data from all of these sources, my sample has a total of 6340 unique banks.

[65] The bank liquidity creation database is available at https://sites.google.com/a/tamu.edu/bouwman/data.
[66] The liquidity creation measures used in this paper are described in the subsection *Variables and Summary Statistics.*

3.2.2 Methods

For an empirical setup, I use the 2007 financial crisis as an exogenous shock that distresses banks, and conduct a test around the crisis. Specifically, I test whether the amount of liquidity created by a bank during the pre-crisis period (2005-2006) increases the riskiness of a bank during the crisis period (2007-2009). I use the following regression specification:

$$Y_i = \alpha + \beta_1 Liquidity\ Created_i + B\ Control\ Variables_i + State\ F.E \qquad (9)$$

where Y_i is bank i's measure of stability during the crisis period and $Liquidity\ Created_i$ is the amount of liquidity created or one of the components of liquidity created by bank i (described in detail in the next subsection) during the pre-crisis period. All control variables, along with the main independent variable, are averaged over the pre-crisis period. I perform a cross-sectional regression with robust standard errors clustered at the bank holding level.

The next test is similar to the one just described, but now, I study whether liquidity creation during 2003-2004 can predict stability during 2005-2006. I refer to the period between 2005 and 2006 as the "false crisis" period. This test will serve to study the relationship between liquidity creation and stability during normal times.

Finally, I study factors that reduce the negative impact of liquidity creation on financial stability of a bank. Specifically, I study the effect of liquid holdings and core deposits on the relationship between liquidity creation and stability. For this, I use the following model:

$$\begin{aligned} Y_i = \alpha + \beta_1 Liquidity\ Created_i & \qquad (10) \\ + \beta_2 Liquidity\ Created_i * Mechanism_i + \beta_3 Mechanism_i & \\ + B\ Control\ Variables_i + State\ F.E & \end{aligned}$$

where $Mechanism_i$ is a dummy variable identifying banks having high liquid holdings or high core deposits.

3.2.3 Variables

a) Bank Stability

I use z-score, standard deviation of ROA (return on assets), and standard deviation of ROE (return on equity) as proxies for stability/riskiness of a bank. Z-score has been widely used in the recent literature as a measure of bank stability (see Laeven and Levine (2009), Houston et al. (2010) and Wang (2014)). It is defined as the sum of the return on assets (ROA) and the capital-asset ratio (CAR) divided by the standard deviation of ROA. Intuitively, the z-score represents the number of standard deviations that a bank's ROA has to drop below mean before equity is depleted (or the bank is insolvent). Specifically,

$$z - score_i = \frac{\frac{1}{T}\sum_{\tau=0}^{T} ROA_{i,\tau} \ + \ \frac{1}{T}\sum_{\tau=0}^{T} CAR_{i,\tau}}{\sigma_0^T (ROA_i)} \tag{11}$$

where *T* is the total number of quarters in the period being considered. ROA is defined as net income over gross total assets (GTA) and CAR is total equity capital over GTA for firm *i* in quarter *t*. In my regressions, I use the natural logarithm of the z-score as the measure for financial stability. Furthermore, to ensure that I have sufficient number of observations to compute my dependent variable, I require that at least half of a bank's pre-crisis and half of the bank's crisis period observations are available.

b) Liquidity Creation

The main independent variable that I use is the liquidity creation measure constructed by Berger and Bouwman (2009). The main measure I use is their preferred "cat fat" measure. Since this measure includes both on-balance sheet and off-balance sheet items, I label it "Overall Liquidity Creation." The authors construct this variable in three steps.

In step 1, they classify all assets, liabilities, and off-balance sheet activities as liquid, semi-liquid, or illiquid. Such classification is based on the ease, cost and time for banks to obtain liquid funds to meet customer demand. For example, cash and securities are classified as liquid assets. On the other hand loans are classified as semi-liquid/illiquid assets depending on their category (thus the label “cat”). For example, since residential mortgages are easier to securitize and dispose of relative to commercial loans, the former loans are classified as semi-liquid, while the latter are classified as illiquid.

Similarly, on the liability side, items such as equity and subordinated debt are classified as illiquid while transaction and savings deposits are classified as liquid. Off-balance sheet (referred to by “fat”), items such as unused commitments, letters of credit etc. are labelled as illiquid, net credit derivatives as semi-liquid, while interest rate and foreign exchange derivatives are labelled as liquid.

In step 2, the authors assign weights to above activities. Since liquidity is created when illiquid assets are transformed into liquid liabilities, positive weights (1/2) are assigned to illiquid assets and liquid liabilities, while negative weights (-1/2) are assigned to liquid assets and illiquid liabilities. Semi-liquid assets and liabilities receive a weight of 0.

Finally, in step 3, the authors take the weighted average value of all activities described in step 1, where weights are as defined in step 2.[67,68]

In addition to the above “Overall Liquidity Creation” (“cat fat”) measure, I will also be studying various components of it as provided by Berger and Bouwman (2009). First, I will be breaking the overall measure into “On-balance sheet” (“catnonfat”) and “Off-balance sheet” liquidity measures. Then, I will be breaking the on-balance sheet measure into “Asset-side” and “Liability-side” liquidity creation.

c) Other Variables

In order to study mechanisms that potentially reduce the negative effect of liquidity creation on stability, I construct dummy variables that identify whether a given bank has high liquid holdings ratio, and high core deposits ratio. Liquidity ratio is total

[67] See Table 4.1 in Berger and Bouwman (2008) for an illustration of the construction of this measure.

[68] Deep and Schaefer (2004) provide an alternate measure for liquidity creation, which they refer to as liquidity transformation gap (“LT gap”). This measure is defined as (liquid liabilities – liquid assets)/total assets. However, as argued in Berger and Bouwman (2009), this measure is not as comprehensive since this definition includes only loans with maturity of one year or less to be liquid, and excludes any off-balance sheet activities.

liquid assets (cash plus fed funds sold plus securities excluding MBS and ABS securities; see Acharya and Mora (2015)) expressed as a fraction of GTA. *Dummy High Liquidity Ratio* takes the value 1 if it has above median liquidity ratio for the sample, otherwise it takes the value 0. Similarly, core deposits assets ratio is the ratio of core deposits (sum of transaction accounts, money market deposit accounts, savings deposits, and time deposits less than $100,000 as defined in Acharya and Mora (2015)) to GTA, and I construct *Dummy High Core Deposit–to-Asset Ratio (CDA)* to identify a bank having above median CDA ratio.

I include several control variables in my regressions. One of the control variables is the pre-crisis level of z-score, which is computed as already described above. Furthermore, I include natural logarithm of total deposits (expressed in 2014 dollars) as a proxy for bank size, asset quality (ratio of non-performing loans to total loans), management quality (overhead costs/GTA), and fee income share (Non-interest income/GTA). The database provided by Berger and Bouwman (2009) also includes information on the location of each bank, where it is headquartered. In particular, city and state information is available. I include state fixed effects to control for state level factors, such as the economic conditions within a state that can potentially affect a bank's stability.

Summary statistics appear in Table 3.1. To ensure that my results are not influenced by outliers, I winsorize all dependent and independent variables at 1%.

3.3 Empirical Results

This section presents empirical results of the paper. First, I study the relationship between liquidity creation and stability. Second, I break liquidity creation into its components to get a better understanding of how it affects stability. Finally, I study factors that affect the relationship between liquidity creation and stability. Specifically, I consider liquid holdings ratio and core deposits to assets ratio as factors that can mitigate the negative effect of liquidity creation on stability.

3.3.1 Liquidity creation and stability

Here, I study the relationship between liquidity creation and stability. The first test is a study around the 2007 financial crisis, and the second test is around "false crisis". I begin with how overall liquidity creation impacts stability. Then, I break this measure into on-balance sheet and off-balance sheet components. Finally, I break the on-balance sheet liquidity creation further into asset-side versus liability side components.

a) Overall liquidity creation

Table 3.2 presents estimation results for model 9. Here, the main independent variable is overall liquidity creation, which includes both on-balance sheet and off-balance sheet activities of a bank. Panel A corresponds to the test around 2007 financial crisis, while panel B corresponds to the test around the false crisis. Under each panel, the table presents results for *log(crisis z-score), sd(ROE),* and *sd(ROA)* as dependent variables.

The results in Table 3.2 show that liquidity creation increases the overall riskiness of a bank during both crisis and normal times. This result is consistent across alternate measures of stability as well. Moreover, the result is economically significant, and the magnitude is similar during both times. For example, a standard deviation increase in overall liquidity creation during the pre-crisis period results in a 5.7% decrease in stability during the crisis period as measured by z-score. This corresponds to a 9.3% of a standard deviation decrease from mean crisis z-score. During normal times, a standard deviation increase in overall liquidity creation results in a 7.5% decrease in stability, and this corresponds to a 15.1% of a standard deviation decrease from mean crisis z-score.

This subsection shows that liquidity creation is a risky activity; it decreases stability of a bank during both good and bad times. However, following subsections will show that different components of liquidity creation affect stability differently depending on overall market conditions. The results will provide insights into how a bank can address stability issues concerning liquidity creation in different market-wide conditions.

b) On-balance sheet versus off-balance sheet

In table 3.3, I break overall liquidity creation into on-balance sheet and off-balance sheet components. Results indicate that the negative relationship between liquidity creation and stability during the crisis period is being driven by off-balance sheet liquidity creation. On the other hand, liquidity created on balance sheet drives the negative relationship between liquidity creation and stability during normal times. While there is some indication that off-balance sheet component may improve stability during normal times, this result is statistically significant for only one of the stability measures and it is not economically significant either. The negative impact of off-balance sheet liquidity creation during bad times more than offsets any potential positive impact during normal times.

Specifically, a standard deviation increase in on-balance sheet liquidity creation results in an 8.5% decrease in stability (17% of a standard deviation decrease from mean crisis z-score) during normal times. On the other hand, a similar increase in off-balance sheet liquidity creation results in a 6.1 % decrease in stability (9.9% of a standard deviation decrease from mean crisis z-score) during bad times, while it increases stability by 1.2% (2.3% of a standard deviation increase from mean crisis z-score) during normal times.

Results pertaining to other alternate measures of stability corroborate the results that use z-score as a measure for stability, except that there is no indication of any positive impact of off-balance sheet component during normal times.

Overall, results indicate that while liquidity creation on balance sheet increases riskiness during normal times, the brunt of the negative impact on stability during crisis period arises due to liquidity created off balance sheet. This is not surprising given that unexpectedly high demand for liquidity led customers to draw down unused commitments during the crisis period, and this aggravated the initial impact of the housing market shock. Also, it is interesting to note that there is not any convincing evidence that off-balance sheet liquidity creation improves stability during normal times.

c) Asset-side versus Liability-side

In Table 3.4, I break on-balance sheet liquidity creation variable into asset-side and liability side components. Results show that asset-side component is negatively related to stability during both crisis and normal times. On the other hand, liability-side liquidity creation improves stability during crisis times, and this result offsets the negative impact of asset-side liquidity creation. However, it hurts stability during normal times. Furthermore, these results are robust to using alternate measures for stability.

These results are economically significant as well. For example, based on z-score as a measure for stability, a standard deviation increase in asset-side liquidity creation results in a 9.0% and 6.6% decrease in stability during bad and normal times respectively (14.6% and 13.2% of a standard deviation decrease from mean crisis z-score respectively). On the other hand, a similar increase in liability-side liquidity creation results in a 5.9 % increase in stability during crisis times (9.6% of a standard deviation increase from mean crisis z-score), while it results in 6.7% decrease in stability during normal times (13.5% of a standard deviation increase from mean crisis z-score).

In unreported table, I also break liability-side liquidity creation into capital asset ratio (total equity/GTA) and liability-side liquidity creation net of capital asset ratio. I find that capital asset ratio (CAR) has a positive impact on stability during both crisis and normal times. So, the negative relationship between liability-side liquidity creation and stability during normal times is primarily being driven by the component that does not include equity.

This highlights the important role played by the liability structure of a bank in determining its stability. High liability side liquidity creation corresponds to high amounts of core deposits, which constitute the most liquid type of funds. These deposits are also the most stable type of funding (see Gatev and Strahan (2006)), since they are insured by the government. On the other hand, wholesale funds (ex. repurchase agreements, federal home loan bank advances, and brokered deposits) and other interest based borrowings that constitute the less liquid liabilities, are uninsured and rate sensitive, which implies that these types of funding dry up in case of market-wide troubles or if the financial condition of the bank deteriorates (Bradley and Shibut (2006)).

This was evident during the financial crisis when banks faced liquidity crisis as investors decided to not roll over funds, leading banks to contract lending (Dagher and Kazimov (2015)). This explains why liability side liquidity creation improves stability during crisis in table 3.4.

During normal times, the use of wholesale funds and interest based borrowings allow banks to attract greater funding by offering competitive rates, and thus to expand their assets. Dagher and Kazimov (2015) document a decline in core deposits to assets ratio since the 1980s, reflecting increased reliance on wholesale funds as opposed to traditional deposit funding. Bradley and Shibut (2006) suggest that this could be attributable to increased competition among banks as well as that from non-bank intermediaries in attracting deposits. While this helps banks to grow during normal times, table 3.4 suggests that it also exposes banks to increased risk.[69]

Overall, the results in IV.1 indicate that liquidity creation is a risky activity. Breaking this variable into its components shows that asset-side liquidity creation increases the overall risk of a bank during both good and bad times. While it helps to use funding from less liquid sources such as wholesale and interest based borrowings during normal times, results indicate that this hurts stability during crisis period. Because of the opposing effects of asset-side and liability side liquidity creation during bad times, the net effect of on-balance sheet liquidity creation is not statistically significant. Much of the riskiness arises due to liquidity creation off balance sheet as customers draw down unused commitments to meet their unexpected liquidity needs. However, off-balance sheet activities do not hurt stability during normal times.

3.3.2 Risk-decreasing factors

In this section, I study how two factors – liquid holdings ratio (liquid assets/GTA) and core deposits to asset ratio (CDA) – interact with liquidity creation and how they

[69] This result is also consistent with Demirguc-Kunt and Huizinga (2010) who find that banks that rely on nondeposit funding are very risky.

affect the negative relationship between liquidity creation and bank stability. Since some of the components of liquidity creation have opposite effects during normal versus bad times, I compare and contrast the impact of these two factors during the two periods in order to better understand their overall effect on a bank's stability.

a) Liquid Holdings Ratio

Table 3.5 presents results for how liquid asset ratio interacts with liquidity creation. Here, I interact the dummy variable that identifies banks having above median liquid holdings ratio, *Dummy High Liquidity Ratio*, with on-balance sheet liquidity creation (LC) and off-balance sheet LC. Panel A tabulates results for the study around the 2007 financial crisis, while panel B tabulates those for the study around the false crisis.

Column 1 in panel A shows that holding high levels of liquid assets does not have a statistically significant effect on the relationship between on-balance sheet LC and stability of a bank. On the other hand, as per Column 2, high levels of liquid assets mitigate the negative effect of off-balance sheet liquidity creation. Since banks create liquidity off-balance sheet by offering lines of credit and commitments, and customers drew down unused commitments to meet their unexpected liquidity needs during the crisis period, it is sensible that banks that held high levels of liquid assets were able to meet such demand for liquidity, thus mitigating the negative impact of off-balance sheet LC on a bank's stability.

Overall, there is a positive effect of liquidity ratio on liquidity creation of a bank, as shown by the positive interaction term between *Dummy High Liquidity Ratio* and *Overall LC* in column 3. Specifically, for a bank having below median liquid holdings ratio, a standard deviation increase in overall LC decreases stability by 10.8%, while for a banking having above median liquid holdings ratio, stability decreases by only half the amount (5.4%).

The results in panel B indicate that during normal times when investment opportunities are better, holding liquid assets is costly since these could be invested for higher returns elsewhere. Column (1) shows that holding high levels of liquid assets amplifies the negative effect of on-balance sheet LC. Similarly, column (2) indicates that holding greater liquid assets takes away money that could be invested in off-balance sheet activities.

Column (3) summarizes the overall cost of holding liquid assets. Specifically, for a bank having below median liquid holdings ratio, a standard deviation increase in overall LC decreases stability by 5.8%, while for a banking having above median liquid holdings ratio, stability decreases by 11.2%.

The above tests show that while there are benefits to holding liquid assets during the crisis period, it is also costly to hold them during normal times. In the final column of both panels in Table 3.5, I study the distribution of liquid holdings ratio to study the sensitivity of banks to holding higher amounts of liquid holdings. Specifically, I construct dummy variables that identify banks having liquid holdings ratio in different quintiles of the sample. During normal times, the cutoff points for liquid holdings ratio that form quintile groups are 0.14, 0.20, 0.27 and 0.37. During bad times, these cutoff points are 0.13, 0.19, 0.25 and 0.35. In this regression, the 1st quintile serves as the base group. Results suggest that during normal times, while banks holding the least amount of liquid assets (1st quintile banks) are the least risky, holding additional amount of liquid assets does not make the bank significantly worse off. On the other hand, results during bad times show that the first quintile banks are the riskiest of all, and holding additional amount of liquid assets makes them significantly better off.

Specifically, during normal times, a standard deviation increase in liquidity creation decreases stability by 8.1% in banks holding liquid assets in the first quintile. The second quintile banks are worse off by 1.3% more. While this group is statistically different from the first quintile group, the difference is not economically significant. Similarly, the the stability of banks in higher quintiles are not economically different from the 1st quintile, and they are not statistically different from the banks in the second quintile.

On the other hand, during crisis times, a standard deviation increase in liquidity creation decreases stability by 14% in banks with liquid holdings ratio in the 1st quintile. The second quintile banks are statistically different from the 1st and they are better off by 2.6% more. Similarly, the 3rd quintile banks are statistically different from the 2nd quintile and are better off by 4%, while 4th quintile banks are better than the 3rd by 2.8%. However, highest group is not statistically different from the 4th. So, there are significant benefits to holding higher amounts of liquid assets during crisis times.

Overall, results suggest that liquid holdings improve the stability of banks during bad times, without making them significantly worse during normal times. This result complements the findings in Shakya (2017), who argues that holding high amounts of liquid assets can mitigate spillovers of risk from one bank to another. Therefore, Shakya (2017) provides a case for liquidity requirements by arguing that the requirements would help contain negative externalities of a bank on others. This paper is complementary in that it compares the costs and benefits of holding liquid assets from a given bank's perspective as opposed to the externalities it imposes on others. By showing that holding liquid assets has higher benefits than costs for a given bank, this paper offers further support to the case for liquidity requirements.

b) Core Deposit to Asset Ratio

In table 3.6, I study how core deposit to asset (CDA) ratio interacts with liquidity creation. I construct *Dummy High CDA*, which identifies banks having above median CDA, and interact this variable with on-balance sheet liquidity creation (LC) and off-balance sheet LC. As before, Panel A tabulates results for the study around the 2007 financial crisis, while panel B tabulates those for the study around false crisis.

Column (1) in panel A indicates that having high core deposit to asset ratio lowers the negative effect of on-balance sheet liquidity creation on bank stability during crisis times. On the other hand, column (2) shows that there is no evidence of any impact of CDA on how off-balance sheet LC affects stability. Overall, high CDA mitigates the negative effect of liquidity creation on stability as shown in column (3). Specifically, for a bank having below median CDA, a standard deviation increase in overall LC decreases stability by 9.3%, while for a bank having above median CDA, stability decreases by 5.3%.

Column (1) in panel B shows that having high core deposits increases the negative effect of on-balance sheet LC during normal times. However, this effect is not economically significant. Specifically, a standard deviation increase in on-balance sheet LC decreases the stability of a bank with above median CDA by 1.5% more than a bank with below median CDA. As per column (2), there is no evidence that CDA affects the relationship between off-balance sheet liquidity creation and stability. Overall, there is an economically small negative effect on stability. Given a standard deviation increase in overall LC, a bank with above median CDA is 1.8% more risky than a bank with below median CDA.

Above results indicate that CDA interacts with liquidity creation to improve the stability of a bank during bad times without any economically significant cost on the stability during normal times. Just as in previous table, I also present results on the distribution of CDA and study a bank's sensitivity to CDA. Again, I construct dummy variables that identify banks having CDA in different quintiles of the sample. During normal times, the cutoff points of CDA that form the quintile groups are 0.62, 0.69, 0.73 and 0.78. During bad times, these cutoff points are 0.59, 0.65, 0.70, and 0.75. As before, the 1st quintile serves as the base group.

During the crisis period, banks in higher quintile groups are significantly better off. Specifically, given a standard deviation increase in overall liquidity creation, stability declines by 20.9, 13.9 and 9.5% in a bank in the 1st, 2nd and 3rd quintile respectively. Other higher quintile groups are not statistically different from one another, suggesting a declining positive effect of CDA. During normal times, stability declines by 5.9 and 8.9% in the 1st and 2nd quintile banks respectively. Higher quintile banks are not statistically different from one another except for the highest quintile group which sees a decline in stability by 12.3%. This indicates that although maintaining too high of a core deposit to asset ratio could potentially hurt stability, increasing CDA does not make a bank significantly worse off during normal times and it has significant benefits during crisis times.

3.4 Conclusion

In this paper, I empirically study the relationship between liquidity creation and stability of a bank. I present further details into the workings of this relationship by comparing results in normal versus bad times, and by breaking liquidity creation into its components – on-balance sheet vs. off-balance sheet, and asset-side vs. liability-side. Specifically, I conduct a study around 2007 financial crisis to understand implications of liquidity creation during bad times. Then I consider a false crisis period and conduct a similar study to draw conclusions regarding normal times.

I find that liquidity creation is a risky activity during both times. However, breaking it into its components reveals the driving forces behind this relationship, and shows that its relations to stability is dependent on overall market conditions. Results show that asset-side liquidity creation hurts stability during both times. However, the implications of liability-side liquidity creation are different for normal versus bad times; it hurts stability during normal times while it increases stability during bad times. Given that high liability side liquidity creation corresponds to higher reliance on traditional deposits, these results reflect the costs and benefits of relying on deposits versus wholesale and retail based liabilities. In regards to off-balance sheet liquidity creation, I find that this is the main driving force behind the negative relationship between liquidity creation and stability during the crisis period. On the other hand, there is no statistically significant impact of this activity during normal times.

Further results show that liquid holdings help mitigate the costs of off-balance sheet liquidity creation during crisis times without significantly imposing costs during normal times. Similarly, core deposits help decrease the costs of on-balance sheet liquidity creation during crisis times without imposing costs during normal times.

Table 3-1. Summary Statistics

This table presents summary statistics for all variables used in the regressions studying the relationship between liquidity creation and stability around the 2007 financial crisis. "Crisis" refers to the period between 2007 and 2009 and "pre-crisis" refers to the period between 2005 and 2006. Stability measures are constructed over the crisis period. Liquidity creation measures and all control variables are averaged over the pre-crisis period. *Crisis Z-score* is computed over the crisis period as the sum of average ROA and average CAR divided by standard deviation of ROA, where *ROA* is return on assets (net income/gross total assets) and *CAR* is capital asset ratio (total equity/gross total assets). *ROE* is return on equity (net income/total equity). Liquidity creation measures are obtained from Berger and Bouwman (2009) and are described in detail in the text. *Asset quality* is non-performing loans/ gross total assets. *Management quality* is overhead costs/ gross total assets, *liquidity ratio* is liquid assets/gross total assets, and *fee income share* is fee income/total income.

Variable	N	Mean	SD	Min	5 pct	Median	95 pct	Max
Stability measures								
crisis Z-score (level)	6340	30.22	18.55	2.14	4.49	27.75	64.39	100.08
log(crisis Z-score)	6340	3.18	0.76	0.76	1.5	3.32	4.16	4.61
sd(crisis ROA)	6340	0.01	0.01	0	0	0	0.02	0.03
sd(crisis ROE)	6340	0.09	0.19	0.01	0.02	0.04	0.31	1.44
Liquidity Creation measures								
Overall LC	6340	0.32	0.18	-0.15	0.01	0.33	0.6	0.73
On-balance sheet LC	6340	0.26	0.15	-0.17	-0.02	0.27	0.48	0.57
Off-balance sheet LC	6340	0.07	0.04	0	0.01	0.06	0.15	0.22
Asset-side LC	6340	0.09	0.15	-0.3	-0.18	0.1	0.31	0.37
Liability-side LC	6340	0.17	0.07	-0.02	0.05	0.16	0.29	0.35
Control Variables								
pre-crisis Zscore (level)	6340	34.14	17.32	9.78	14.85	30.44	68.05	110.53
log(pre-crisis Zscore)	6340	3.42	0.46	2.28	2.7	3.42	4.22	4.71
sd(pre-crisis ROA)	6340	0	0	0	0	0	0.01	0.02
sd(pre-crisis ROE)	6340	0.04	0.02	0.01	0.02	0.04	0.08	0.11
log(Deposits)	6340	11.71	1.14	9.89	10.14	11.56	13.8	15.85
Asset Quality	6340	0.01	0.01	0	0	0.01	0.03	0.05
Management Quality	6340	0.02	0.01	0.01	0.01	0.02	0.03	0.05
Liquidity Ratio	6340	0.25	0.14	0.04	0.07	0.22	0.52	0.69
Fee Income Share	6340	0.11	0.07	0.01	0.03	0.1	0.23	0.43

Table 3-2: Overall Liquidity Creation

This table studies the relationship between overall liquidity creation and stability of a bank. Panel A conducts a study around the 2007 financial crisis (2007-2009 is the crisis period, 2005-2006 is the pre-crisis period). Panel B conducts a study around a false crisis period (2005-2006 is the false crisis period, 2003-2004 is the pre-crisis period). The reported estimates are from the regression in model (9). The dependent variable is *log(z-score)*, *sd(ROE)* (standard deviation of return on equity), or *sd(ROA)* (standard deviation of return on assets) during the crisis period. *sd(ROA)* is scaled up by a factor of 10. The main independent variable is *Overall LC*, which is the liquidity creation measure that includes both on-balance sheet and off-balance sheet activities of a bank during the pre-crisis period. All variables including control variables are computed as described in the text, and all independent variables are averaged over the pre-crisis period. All regressions include state fixed effects. Standard errors are robust and clustered at the bank holding company level (bank level if independent), and are reported in parenthesis. *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	Panel A (Crisis)			**Panel B (False Crisis)**		
	(1)	(2)	(3)	(4)	(5)	(6)
	log(crisis zscore)	sd(ROE)	sd(ROA)	log(crisis zscore)	sd(ROE)	sd(ROA)
Overall LC	-0.309***	0.045**	0.023***	-0.401***	0.016***	0.015***
	(0.081)	(0.023)	(0.006)	(0.043)	(0.002)	(0.002)
log(pre-crisis Zscore)	0.425***			0.515***		
	(0.024)			(0.014)		
sd(pre-crisis ROE)		0.755***			0.541***	
		(0.173)			(0.018)	
sd(pre-crisis ROA)			0.441***			0.416***
			(0.037)			(0.017)
log(Deposits)	-0.074***	0.014***	0.004***	0.012**	-0.000*	-0.001***
	(0.012)	(0.003)	(0.001)	(0.006)	(0.000)	(0.000)
Asset Quality	-3.580***	0.772***	0.411***	0.269	-0.025	0.093***
	(1.075)	(0.239)	(0.074)	(0.537)	(0.025)	(0.025)
Management Quality	-9.657***	2.788***	0.177	14.738***	-0.490***	-0.869***
	(2.301)	(0.720)	(0.176)	(1.499)	(0.069)	(0.071)
Liquidity Ratio	0.593***	-0.065**	-0.022***	0.154***	-0.004*	-0.001
	(0.093)	(0.026)	(0.007)	(0.050)	(0.002)	(0.002)
Fee Income Share	0.936***	-0.271***	-0.039**	-0.944***	0.032***	0.052***
	(0.196)	(0.056)	(0.016)	(0.100)	(0.005)	(0.005)
State F.E	Y	Y	Y	Y	Y	Y
Observations	6337	6337	6337	6753	6753	6753
Adjusted Within R-squared	0.147	0.027	0.06	0.389	0.389	0.304

Table 3.3: On-Balance Sheet vs Off-Balance Sheet Liquidity Creation

This table breaks overall liquidity creation into on-balance sheet and off-balance sheet components and studies how they relate to the stability of a bank. Panel A conducts a study around the 2007 financial crisis (2007-2009 is the crisis period, 2005-2006 is the pre-crisis period). Panel B conducts a study around a false crisis period (2005-2006 is the false crisis period, 2003-2004 is the pre-crisis period). The reported estimates are from the regression in model (9). The dependent variable is *log(z-score), sd(ROE)* (standard deviation of return on equity), or *sd(ROA)* (standard deviation of return on assets) during the crisis period. *sd(ROA)* is scaled up by a factor of 10. The main independent variables are *On-balance sheet LC* and *Off-balance sheet LC,* which are the on-balance sheet and off-balance sheet components of overall liquidity creation, measured during the pre-crisis period. All variables including control variables are computed as described in the text, and all independent variables are averaged over the pre-crisis period. All regressions include state fixed effects. Standard errors are robust and clustered at the bank holding company level (bank level if independent), and are reported in parenthesis. *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	Panel A (Crisis)			**Panel B (False Crisis)**		
	(1)	(2)	(3)	(4)	(5)	(6)
	log(crisis zscore)	sd(ROE)	sd(ROA)	log(crisis zscore)	sd(ROE)	sd(ROA)
On-balance sheet LC	-0.074	-0.03	-0.001	-0.541***	0.020***	0.019***
	(0.099)	(0.029)	(0.008)	(0.051)	(0.002)	(0.002)
Off-balance sheet LC	-1.476***	0.435***	0.136***	0.289*	-0.003	-0.008
	(0.308)	(0.101)	(0.026)	(0.173)	(0.010)	(0.010)
State F.E	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Observations	6337	6337	6337	6753	6753	6753
Adjusted Within R-squared	0.149	0.032	0.065	0.391	0.391	0.305

Table 3.4: Asset-side vs Liability-side Liquidity Creation

This table breaks overall liquidity creation into asset-side and liability-side components and studies how they relate to the stability of a bank. Panel A conducts a study around the 2007 financial crisis (2007-2009 is the crisis period, 2005-2006 is the pre-crisis period). Panel B conducts a study around a false crisis period (2005-2006 is the false crisis period, 2003-2004 is the pre-crisis period). The reported estimates are from the regression in model (9). The dependent variable is *log(z-score)*, *sd(ROE)* (standard deviation of return on equity), or *sd(ROA)* (standard deviation of return on assets) during the crisis period. *sd(ROA)* is scaled up by a factor of 10. The main independent variables are *Asset-side LC* and *Liability-side LC*, which are the asset side and liability side components of overall liquidity creation, measured during the pre-crisis period. All variables including control variables are computed as described in the text, and all independent variables are averaged over the pre-crisis period. All regressions include state fixed effects. Standard errors are robust and clustered at the bank holding company level (bank level if independent), and are reported in parenthesis. *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	Panel A (Crisis)			**Panel B (False Crisis)**		
	(1)	(2)	(3)	(4)	(5)	(6)
	log(crisis zscore)	sd(ROE)	sd(ROA)	log(crisis zscore)	sd(ROE)	sd(ROA)
Asset-side LC	-0.572***	0.124***	0.051***	-0.424***	0.018***	0.022***
	(0.120)	(0.032)	(0.008)	(0.057)	(0.003)	(0.003)
Liability-side LC	0.818***	-0.312***	-0.091***	-0.926***	0.030***	0.016***
	(0.163)	(0.051)	(0.013)	(0.086)	(0.004)	(0.004)
Off-balance sheet LC	-1.101***	0.320***	0.103***	0.209	-0.001	-0.011
	(0.307)	(0.101)	(0.026)	(0.175)	(0.010)	(0.010)
State F.E	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Observations	6337	6337	6337	6753	6753	6753
Adjusted Within R-squared	0.159	0.047	0.085	0.396	0.393	0.306

Table 3.5: Liquid Holdings Ratio

This table studies how liquid holdings ratio of a bank affects the relationship between liquidity creation and stability of a bank. Panel A conducts a study around the 2007 financial crisis (2007-2009 is the crisis period, 2005-2006 is the pre-crisis period). Panel B conducts a study around a false crisis period (2005-2006 is the false crisis period, 2003-2004 is the pre-crisis period). The estimates are regression results of (1) in which the dependent variable is *log(z-score)*, measured during the crisis period. The independent variables are *Overall LC* and its components – *On-balance sheet LC* and *Off-balance sheet LC*. The independent variables are interacted with *Dummy High Liquidity Ratio*, which identifies banks having above median liquid holdings ratio (liquid assets/gross total assets). *Dummy Liquidity Ratio in 2nd Quintile* identifies banks having this ratio in the 2nd quintile of the distribution, and other dummy variables are constructed similarly to identify banks in higher quintiles. All variables including control variables are computed as described in the text, and all independent variables are averaged over the pre-crisis period. All regressions include state fixed effects. Standard errors are robust and clustered at the bank holding company level (bank level if independent), and are reported in parenthesis. *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	Panel A (Crisis)			
	log(crisis z-score)			
	(1)	(2)	(3)	(4)
On-balance sheet LC	-0.364***	-0.246***		
	(0.130)	(0.087)		
On-balance sheet LC * Dummy High Liquidity Ratio	0.215			
	(0.139)			
Off-balance sheet LC	-1.403***	-1.874***		
	(0.311)	(0.361)		
Off-balance sheet LC * Dummy High Liquidity Ratio		1.084**		
		(0.463)		
Overall LC			-0.568***	-0.727***
			(0.101)	(0.076)
Overall LC * Dummy High Liquidity Ratio			0.278**	
			(0.115)	
Overall LC * Dummy Liquidity Ratio in 2nd Quintile				0.143**
				(0.070)
Overall LC * Dummy Liquidity Ratio in 3rd Quintile				0.348***
				(0.073)
Overall LC * Dummy Liquidity Ratio in 4th Quintile				0.495***
				(0.080)
Overall LC * Dummy Liquidity Ratio in 5th Quintile				0.529***
				(0.122)
State F.E	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Observations	6337	6337	6337	6337
Adjusted Within R-squared	0.149	0.15	0.148	0.149

	Panel B (False Crisis)			
	log(crisis z-score)			
	(1)	(2)	(3)	(4)
On-balance sheet LC	-0.435***	-0.593***		
	(0.062)	(0.046)		
On-balance sheet LC * Dummy High Liquidity Ratio	-0.285***			
	(0.071)			
Off-balance sheet LC	0.236	0.490**		
	(0.174)	(0.203)		
Off-balance sheet LC * Dummy High Liquidity Ratio		-0.560**		
		(0.251)		
Overall LC			-0.315***	-0.435***
			(0.051)	(0.035)
Overall LC * Dummy High Liquidity Ratio			-0.275***	
			(0.061)	
Overall LC * Dummy Liquidity Ratio in 2nd Quintile				-0.070**
				(0.030)
Overall LC * Dummy Liquidity Ratio in 3rd Quintile				-0.101***
				(0.035)
Overall LC * Dummy Liquidity Ratio in 4th Quintile				-0.084**
				(0.041)
Overall LC * Dummy Liquidity Ratio in 5th Quintile				-0.05
				(0.072)
State F.E	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Observations	6753	6753	6753	6753
Adjusted Within R-squared	0.392	0.391	0.39	0.388

Table 3.6: Core Deposit-to-Asset Ratio

This table studies how core deposit to asset ratio of a bank affects the relationship between liquidity creation and stability of a bank. Panel A conducts a study around the 2007 financial crisis (2007-2009 is the crisis period, 2005-2006 is the pre-crisis period). Panel B conducts a study around a false crisis period (2005-2006 is the false crisis period, 2003-2004 is the pre-crisis period). The estimates are regression results of (1) in which the dependent variable is *log(z-score)*, measured during the crisis period. The independent variables are *Overall LC* and its components – *On-balance sheet LC* and *Off-balance sheet LC*. The independent variables are interacted with *Dummy High CDA*, which identifies banks having above median core deposit to asset ratio. *Dummy CDA in 2nd Quintile* identifies banks having this ratio in the 2nd quintile of the distribution, and other dummy variables are constructed similarly to identify banks in higher quintiles. All variables including control variables are computed as described in the text, and all independent variables are averaged over the pre-crisis period. All regressions include state fixed effects. Standard errors are robust and clustered at the bank holding company level (bank level if independent), and are reported in parenthesis. *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	Panel A (Crisis)			
	log(crisis z-score)			
	(1)	(2)	(3)	(4)
On-balance sheet LC	-0.359***	-0.262**		
	(0.117)	(0.102)		
On-balance sheet LC * Dummy High CDA	0.266**			
	(0.110)			
Off-balance sheet LC	-1.194***	-1.443***		
	(0.312)	(0.376)		
Off-balance sheet LC * Dummy High CDA		0.702		
		(0.432)		
Overall LC			-0.494***	-0.799***
			(0.095)	(0.106)
Overall LC * Dummy High CDA			0.207**	
			(0.094)	
Overall LC * Dummy CDA in 2nd Quintile				0.327***
				(0.088)
Overall LC * Dummy CDA in 3rd Quintile				0.527***
				(0.085)
Overall LC * Dummy CDA in 4th Quintile				0.608***
				(0.086)
Overall LC * Dummy CDA in 5th Quintile				0.627***
				(0.089)
State F.E	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Observations	6337	6337	6337	6337
Adjusted Within R-squared	0.156	0.155	0.154	0.159

	Panel B (False Crisis)			
	log(crisis z-score)			
	(1)	(2)	(3)	(4)
On-balance sheet LC	-0.423***	-0.460***		
	(0.059)	(0.052)		
On-balance sheet LC * Dummy High CDA	-0.098*			
	(0.056)			
Off-balance sheet LC	0.135	0.253		
	(0.172)	(0.186)		
Off-balance sheet LC * Dummy High CDA		-0.321		
		(0.231)		
Overall LC			-0.315***	-0.185***
			(0.048)	(0.050)
Overall LC * Dummy High CDA			-0.097**	
			(0.048)	
Overall LC * Dummy CDA in 2nd Quintile				-0.157***
				(0.039)
Overall LC * Dummy CDA in 3rd Quintile				-0.182***
				(0.039)
Overall LC * Dummy CDA in 4th Quintile				-0.224***
				(0.040)
Overall LC * Dummy CDA in 5th Quintile				-0.370***
				(0.043)
State F.E	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Observations	6753	6753	6753	6753
Adjusted Within R-squared	0.395	0.395	0.394	0.396

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VITA

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EDUCATION

Ph.D., Finance, Pennsylvania State University	2018
M.A., Mathematics, Saint Louis University	2013
M.S., Business Administration (Finance), Washington University in St. Louis	2011
B.A., Mathematics and Physics, Hanover College	2007

RESEARCH INTERESTS

Banking and Financial Institutions, Banking Regulation, Financial Stability, Empirical Corporate Finance

WORKING PAPERS

Interbank Connections and Financial Stability
The Impact of Liquidity Requirements on Loan Contract Terms (with Jess Cornaggia)
Bank Liquidity Creation and Financial Stability

SERVICE

Ad hoc referee for *Frontiers of Economics in China*, *Journal of Financial Stability*, *Pacific-Basin Finance Journal*, *The Quarterly Journal of Finance*, *Quarterly Journal of Finance and Accounting*, *Real Estate Economics*

AWARDS

AFA Doctoral Student Travel Grant (2017), Smeal College of Business Assistantship and Fellowship (2013-2018), Saint Louis University Teaching Assistantship (2011-2013), Olin Business School Fellowship (2009-2011), John Yarnelle Mathematics Prize, Richard L. Conklin Award in Physics, R. Earl Martin Physics Award (2005-2007), Hanover College Merit Scholarship (2003-2007)

TEACHING EXPERIENCE

Instructor:

Penn State: Financial Management of the Business Enterprise, Security Analysis and portfolio Management	Summer 2014 & 2016
Saint Louis University: Finite Mathematics, Pre-Calculus, College Algebra, Statistics with Computers	Spring 2012- Spring 2013

Teaching Assistant:

Penn State: Security Analysis and Portfolio Management	2013 - 2018
Saint Louis University: Help Sessions (all undergraduate math courses)	Fall 2011
Washington University in St. Louis: Options and Futures (graduate course), Derivative Securities (grad), Investments (grad/undergrad), Advanced Financial Management (undergrad)	2010-2011

OTHER WORK EXPERIENCE

Research Assistant for Prof. Jingzhi Huang, Prof. Joel Vanden, Penn State	2013 – 2018, 2016 –2017
Intern, Morgan Stanley Smith Barney, Purchase, NY	Summer 2009
Quantitative Analyst, Sandler O'Neill and Partners, New York, NY	2007-2008