Interbank Connections and Financial Stability[1]

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ABSTRACT

In this paper, I study how interconnectedness of a bank is related to its financial stability. In addition, I ask what mechanisms amplify/mitigate such relationship. Using a detailed US home loan database, I consider linkages that are formed between banks due to exposure to common housing markets. I then investigate the role of such linkages in explaining financial stability around the 2007 financial crisis. The main result of the paper is that in the event of a large shock, interlinkages facilitate contagion of distress and make banks riskier. In the absence of a shock (i.e., during the pre-crisis period), there is no evidence of such negative relationship between interconnections and stability. Furthermore, I provide evidence that high exposure to leverage and securitization activity of *other* banks exacerbate the contagion effect of interlinks, while exposure to liquidity ratio of other banks mitigates this effect.

I. INTRODUCTION

In the wake of the 2007-2009 financial crisis, governments around the globe convened for a coordinated effort to manage the fallout of the crisis, and in the forefront of the efforts were ways to address the intertwined structure of the financial system and the risks of contagion borne by it. The aftermath of the crisis underscored the role played by the complexities of interconnections in shaping systemic risk, and their negative implications for the real economy as well. To address this problem, the Basel Committee issued a framework of higher regulatory capital standards for Global Systemically Important Banks (GSIB) in November 2011, and as Yellen (2013) notes, the indicators of interconnectedness accounted for a significant portion of the overall score that determined whether an institution should be subject to higher requirements[3].

Given the attention that interconnectedness of the banking system has received in recent years, I first ask in this paper how a bank's degree of interconnections is related to its financial stability. Second, I ask if there are any mechanisms that amplify/mitigate this relationship. In particular, I consider a bank's exposure to leverage, securitization activity and liquid holdings of *other* banks as potential mechanisms that can affect this relationship.

Recently, there has been a surge in theoretical and empirical work to study the relationship between interconnectedness and financial stability. However, Glasserman and Young (2015), in a survey on the extant literature in the area, argue that existing empirical work has not produced a convincing link between the two. One of the reasons for this is that empirical work has focused on interlinkages formed between banks due to interbank lending, and the main challenge in such approach is the limited access to bilateral loan exposures of banks. While

[3] Bank of International Settlements (2009).

information on aggregate amounts lent and borrowed by a bank are publicly available, details on who the amounts are lent to/borrowed from are not public information, and this information is important in constructing appropriate linkages between banks. As Upper (2011) notes, many have, therefore, resorted to simulation techniques. However, these methods tend to produce biased results due to the assumptions that have to be made in applying them.

This paper attempts to fill the gap in the empirical literature by considering interlinkages formed due to exposure to common housing markets instead. There are multiple phenomena of contagion besides direct loss spillovers, such as contagion through mark-to-market losses, funding runs, information contagion (spread of fear of losses following a default), and contagion through correlation (see Glasserman and Young (2015)). Common exposure to local housing markets is one of them and an important one since the 2007 financial crisis was initiated by troubles in the housing industry. The home loan database available from Home Mortgage Disclosure Act (HMDA) provides detailed information on the geographic location of properties, which allows me to construct bilateral loan exposures of banks through a common local market.

Specifically, I say that two banks are linked if they originate loans in the same Metropolitan Statistical Area. When there is a negative housing market shock, one potential mechanism for contagion of distress occurring from one bank to another is through common collateral holdings. If, for example, bank A is especially distressed as a result of a shock, it is going to contract mortgage lending. If other banks are not able to pick up the slack – as is likely in the event of a large shock – local housing activity is going to decline. This then accelerates the decline in house prices initiated by the shock, which implies that other banks holding mortgage loans in the same area suffer a further decline in the value of the collateral in their portfolio. Thus, the credit exposure of other banks increases. Another possibility is that investors are wary of availing funds not just to bank A but also to nearby banks, thus forcing these banks to contract lending. This is a likely scenario under information contagion, whereby investors are fearful of spread of losses following losses at one financial institution. As argued before, lending contraction has implications on house price levels and the health of the banks in the area. [4]

The study of the relationship between network structure of a financial system and the system's stability involves a tradeoff between different forces of costs and benefits of interconnections. On one hand, diversification of risk exposures is inherent in a banking network, which can have a positive impact on the stability of a bank. For example, in the housing context considered here, geographic diversification could allow a bank to reduce the impact of local market shocks. On the other hand, in the event of a negative shock, the same interconnections could serve as channels of contagion. Which force dominates is an empirical question.

To answer this question, I design my study around the 2007 financial crisis, which was a shock of substantial magnitude to the financial system. I study whether a bank's interconnectedness during the pre-crisis period can explain its stability during the crisis period. For each bank, I measure its interconnectedness using a weighted measure of degree of interconnections. Since interlinkages arise due to loan exposures to other banks through common MSAs (housing markets), the weight used for each linkage of a given bank with another reflects its total loan exposure to the MSAs where the two overlap. Thus, the degree of links measure is the sum of the loan exposures of a bank to each of the other banks with which it is linked.[5] I find

[4] Literature provides some empirical evidence supporting this mechanism of the spread of distress. For example, Rajan and Ramcharan (2016) find that reduction in local financial intermediation capacity depresses local land prices, and further results in distress in nearby banks. Similarly, Agarwal, Ambrose, and Yildirim (2015) argue that foreclosures facilitate spillover by negatively impacting nearby property values (by increasing the supply of houses or by lowering property maintenance). They show that mortgage default risk can spread from subprime mortgages to prime mortgages through such externalities associated with subprime foreclosures.

[5] The degree of links measure is described in detail in section IV.

that a higher degree of interconnections makes a bank riskier during the crisis period, and this result is statistically and economically significant. I find that a standard deviation increase in degree of links from the mean decreases stability by 5.1% in large banks (above $1 billion in size), while it decreases stability by 7.5% in small banks (having size up to $1 billion).[6] However, I find no evidence of such effect during normal times.

Next, I investigate average levels of leverage and securitization activity of *other* banks as possible mechanisms that magnify the contagion effect of interconnections and the liquidity ratios of *other* banks as a possible mechanism that mitigates this effect. To capture such mechanisms, I compute the weighted average exposure of a bank to these mechanisms in the MSAs (housing markets) where it originates loans. The weights reflect the bank's loan exposures in the MSAs.

The intuition for using exposure to leverage of other banks as a contagion-amplifying mechanism comes from the idea that highly levered banks are less capable of absorbing negative shocks, and thus amplify the initial impact of the shock that is then transmitted to other banks through interlinks. I find that leverage of other banks increases the magnitude of the negative relationship between interconnections and bank stability, and that this effect is driven by small size banks, revealing their greater vulnerability to contagion through this channel. In particular, a standard deviation increase in the degree of links from the mean implies that the stability of a small bank decreases by 3.9% in a bank with low leverage exposure (below median exposure), while it declines with 10% in a bank with high leverage exposure.

Next, the securitization market expanded substantially prior to the financial crisis, and many studies have linked securitization activity to the deterioration in loan quality and to the

[6] These numbers are based on the impact of interconnections on z-score as a measure for bank stability. *Data and Methods* section provides a description of how z-score is computed.

onset of the crisis. To the extent that securitization leads to the origination of poor quality loans, banks that are involved in greater securitization activity should be affected to a greater extent by a negative shock, thereby amplifying the magnitude of the initial shock. Results show that exposure to securitization activity of other banks magnifies the contagion effect of interconnections, and this result is significant especially for large banks that were the major players in the securitization market. A standard deviation increase in the degree of links from the mean implies that the stability of a large bank decreases by 15.2% in a bank with high exposure to securitization activity of other banks, while this effect is not significant for a bank having low such exposure.

Finally, liquid holdings help absorb the effects of negative shocks and decrease the need to fire-sell assets for additional liquidity, which would otherwise have spillover effects on other banks. The importance of holding liquid assets was apparent during the 2007 financial crisis, and in response, the Basel Committee introduced a new liquidity regulation, which included requirements on Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR). LCR has already been introduced in the United States effective January 2015. I find that exposure to high levels of liquid holdings by other banks mitigates the contagion effect of interconnections. In particular, a standard deviation increase in the degree of links from the mean implies that the stability of an average bank decreases by 15.8% in a bank with low exposure to liquid holdings of other banks, while it declines by only 5.1% in a bank that has high such exposure.

This paper has potential policy implications. First, I find that costs of interconnectedness are high only during the crisis period, and that they do not substantially affect the stability of banks during normal times. Second, it identifies securitization and leverage as important mechanisms that amplify the contagion effect of interconnections. While leverage exposure plays a more dominant role in distressing small banks, securitization exposure plays a dominant role in distressing large banks. Third, this paper underscores the importance of liquid holdings of banks in mitigating externalities of interconnections, and this effect is significant in both size categories of banks. Such findings of when interconnectedness is costly and what mechanisms amplify/mitigate these costs help policymakers develop better ways of addressing issues pertaining to interconnectedness of a financial system.

The rest of the paper is organized as follows. Section II reviews related literature. Section III develops the hypothesis for the paper, while section IV describes data and variables used. Section V discusses the main empirical results of the paper. Finally, section VI concludes.

II. LITERATURE REVIEW

This section briefly reviews the literature on financial networks and their role in contagion of negative shocks (see Glasserman and Young (2015) for a detailed survey). While the literature has primarily focused on linkages formed due to interbank lending, the ideas can be applied to other network settings, and have provided important insights for my paper.

A pioneering work in the literature that sets the stage for thinking about the relationship between interconnections and stability is the theoretical treatment of the issue in Allen and Gale (1999), who study contagion of liquidity shocks in a network based on interbank lending. They argue that it is in the best interest of banks to hold claims on one another ex-ante to insure themselves against liquidity shocks, but such a system can also be fragile because interbank linkages facilitate propagation of the initial shock.[7,8] Similarly, Eisenberg and Noe (2001)

[7] The authors argue that liquidity shocks faced by different banks are imperfectly correlated so that holding interregional claims on one another helps them insure against such shocks; lending by banks with excess liquidity to banks with a liquidity shortage can prevent early liquidation of assets.

provide an important framework for analyzing the spread of loss in a network, and this setting has served as a starting point for many subsequent papers in the area (see Rogers and Veraart (2013), Glasserman and Young (2015), Cifuentes, Ferrucci, and Shin (2005)).

Other theoretical work has provided different perspectives and has provided additional details to the theory of financial networks. For example, studies such as Brusco and Castiglionesi (2007) and Zawadowski (2013) (in different settings) incorporate moral hazard, and argue how risk diversification benefits of interconnections may incentivize banks to take higher risks.[9] Gai, Haldane, and Kapadia (2011) study implications of an interbank network in a funding run scenario, while other papers model other different phenomena of contagion that amplify the externalities of interbank linkages (see Cifuentes, Ferrucci, and Shin (2005) for contagion through fire sale of assets and common asset holdings, and Glasserman and Young (2015) for information contagion arising from the loss of confidence in the creditworthiness of financial institutions).

While above papers emphasize the potential contagion effect through interconnections during a stress scenario, Leitner (2005) develop a model where financial linkages not only spread contagion, but (in certain cases) also provide incentives to liquid banks to bail out illiquid banks in order to avoid contagion. Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015), on the other hand, argue that the extent of contagion through a financial network depends on the magnitude of a negative shock. As long as the shock is below a certain cut-off point, interconnections (through interbank liabilities) enhance stability. Beyond that point, these interconnections help in the

[8] The authors compare different network topologies, and show that a ring network (in which each bank borrows from exactly one other bank) is fragile since losses in the value of a bank's liabilities are concentrated in only one other bank, while a complete network (in which every bank lends to every other bank) is more robust because losses are diluted among other banks.

[9] Brusco and Castiglionesi (2007) work in the Allen and Gale (1999) model, and arrive at different results which show that a complete network structure is less stable than a ring structure.

spread of distress. Glasserman and Young (2015) highlight the importance of size, leverage, and asset quality instead in assessing contagiousness of banks. Their model simulations further suggest that the spread of losses in a network is modest, and that other mechanisms such as bankruptcy costs and loss of confidence are needed to amplify the contagion effect to cause substantial losses.

This result in Glasserman and Young (2015) is, in fact, consistent with other simulation work that has been done in the literature to study the spread of distress through an interbank network. Because detailed information on interbank exposures is not publicly available, much of the empirical work has focused on simulation methodologies to study transmission of shocks. Upper (2011) provides a survey of this literature on simulation work. He concludes that the literature generally suggests that contagion due to interbank exposures is likely to be rare (e.g. Furfine (2003), Amundsen and Arnt (2005)); however, if it does take place, it could have a sizable negative impact on the total assets of a banking system (e.g. Upper and Worms (2004), Elsinger, Lehar, and Summer (2006)). Upper (2011) does, however, caution the readers that the results of extreme contagion could be due to assumptions made in the simulation work.

In a recent paper, Iyer and Peydró (2011) provide empirical evidence on contagion occurring through interbank lending by exploiting the failure of a large Indian bank, and showing that this failure leads to large withdrawal of deposits in other banks having highest exposure to the failed bank. However, they do not establish a direct link between network structure and stability, which I study in this paper.

As Glasserman and Young (2015) notes, other methods have been developed to get around the issue of limited availability of data in the study of banking networks. These include defining a network through comovements in stock prices (developed in Billio et al. (2012)) and using variance decompositions to infer cross variable influences (developed in Diebold and Yılmaz (2014)). However, they argue that it is not clear what the underlying mechanism is for these correlated market data. In this paper, I define a network using linkages formed between banks due to exposure to a common housing market, in which case the spread of distress from one bank to another occurs through the impact on local house prices and common collateral holdings as explained earlier.

III. HYPOTHESES

This section outlines the main hypotheses in my paper. The first hypothesis concerns the relationship between interconnectedness of a bank and its stability. Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015) emphasize the importance of the magnitude of a negative shock in the study of this relationship. They argue that as long as the magnitude of the shock is below a certain threshold, a more densely connected network structure leads to improved financial stability, owing to the benefits of risk diversification. However, if the magnitude of the shock crosses the threshold, these linkages facilitate contagion of distress, thus leading to a more fragile system. Following this intuition, I first test the impact of interconnections on bank stability around the 2007 financial crisis. As per theory, higher degree of links maintained by banks during the pre-crisis period should result in greater instability during the crisis period. Therefore, hypothesis I is as follows:

Hypothesis 1: Higher degree of interconnections during the pre-crisis period results in greater instability during the crisis period.

Next, I am interested in exploring mechanisms that amplify/mitigate the effect of interconnections on stability. Specifically, I investigate the average levels of leverage and securitization activity of other banks with which the bank in question is linked as possible mechanisms that magnify the contagion effect of interconnections. Then I consider the average level of liquid holdings of other banks as a possible mechanism that mitigates this effect.

The motivation for studying leverage as a possible contagion-amplifying mechanism comes from Goel, Song, and Thakor (2014), who argue that a bank's credit exposure can increase with leverage choices of other banks. The intuition is that highly levered banks are less capable of absorbing negative shocks such that 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, and accelerates the decrease in house prices initiated by the negative shock. Such decline in house prices then increases the otherwise independent bank's credit risk exposure. Therefore, as per this theory, high exposure to leverage of other banks should exacerbate the contagion of distress through interconnections during the crisis period. Similarly, Glasserman and Young (2015) also suggest that spillover effects are stronger when they originate at banks with high leverage. This leads to my second hypothesis:

Hypothesis 2: Exposure to high levels of leverage of *other* banks amplifies the costs of interconnections for a given bank.

My third hypothesis concerns the contagion-amplifying mechanism through exposure to securitization activity of other banks. 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 secondary market for subprime lending did shut down when the housing market crashed in 2007. To the extent that securitization leads to poor quality loans, banks that are exposed to higher levels of securitization activities of other banks should be more vulnerable to the contagion effect of interconnections. Hypothesis 3 is as follows:

Hypothesis 3: Exposure to high levels of securitization activity of *other* banks amplifies the costs of interconnections for a given bank.

Finally, my fourth hypothesis concerns the contagion-mitigating effect of liquid holdings of other banks. Stein (2013) argues that a lack of liquid assets can increase run risk, and can lead banks to fire-sell illiquid assets, which further results in contraction in credit availability and spillover effects to other banks. Cifuentes, Ferrucci, and Shin (2005), in their study of contagion of distress in an interbank network, model fire sales as a mechanism that magnifies such contagion effect, and suggest that liquidity requirements can help mitigate this effect. Similarly, Gai, Haldane, and Kapadia (2011) analyze liquidity shocks in an interbank network, and their model simulations show that an increase in liquid asset holdings makes the system less susceptible to liquidity crises. Therefore, as per theory, banks that are exposed to other banks holding higher levels of liquid assets should be less affected by the contagion effect of interconnections. Hypothesis 4 can be stated as follows:

Hypothesis 4: Exposure to high levels of liquid holdings of *other* banks mitigates the costs of interconnections for a given bank.

IV. DATA AND METHODS

IV.1 Data and Sample

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 information. Congress enacted HMDA in 1975 to improve public reporting of mortgage loans. (The law was enacted to ensure that lenders were serving the housing needs of their communities in an indiscriminatory way.) US financial institutions are required to report HMDA data to their regulators if they meet certain criteria, such as having assets beyond some threshold. This is an annual database and contains information on loan applications (regardless of whether or not they were approved), applicant quality and borrower demographics. It also provides lender details, loan specifics such as loan amount and interest rates charged, as well as property information such as the geographical location of the property.

For this paper, I obtain a subsample of loans that were originated between 2005 and 2009, which are the years surrounding the financial crisis. I filter for loans that are (i) conventional, (ii) not sold (as of the calendar year-end) or sold to an affiliate, and (iii) have loan amounts greater than $50,000. Then, I supplement this subsample from the HMDA database with further lender details from the HMDA Lender file[10]. This file matches every lender who has filed a HMDA report on and after 1993 with the identification code (RSSD) used by the Federal

[10] I thank Robert Avery at Federal Housing Finance Agency (FHFA) for providing me with the HMDA Lender file.

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, 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 1348 unique banks. I also split my sample into large and small banks to study the 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.[11] The final sample has 359 large banks and 989 small banks.

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

IV.2 Methods

In order to study whether interconnections between banks facilitate contagion of distress, 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 degree of interconnections that a bank maintains 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:

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

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

In addition to studying whether interconnectedness is negatively related to the stability of a bank, I also study whether it can explain a high decline in the measure for stability. For this, I define a high decline in stability as any percent change in the stability measure (from pre-crisis to crisis period) that is smaller than the mean for the sample. Then, I study whether the probability of a high decline in stability increases as interconnectedness of a bank increases. Specifically, I use the probit model as follows:

$$high\ decline\ in\ Y_i = \alpha + \beta_1 Degree\ Links_i + B\ Control\ Variables_i \qquad (2)$$

where *high decline in* Y_i is a dummy variable taking the value 1 if the percent change in the stability measure from pre-crisis to crisis period is smaller than the mean for the sample.

When I investigate mechanisms that may amplify or mitigate the contagion effect of interconnections, I estimate the following model:

$$Y_i = \alpha + \beta_1 \, Degree\ Links_i + \beta_2 Amplifier + \beta_3 \, Degree\ Links_i \ X \ Amplifier + B \ Control\ Variables_i \tag{3}$$

where Y_i is the stability measure or the dummy variable identifying a high decline in the stability measure, $Amplifier$ is exposure to leverage, securitization activity, or liquid holdings of *other* banks in the housing markets where bank *i* originates loans. The coefficient on the interaction term is of interest here in understanding whether the mechanism being considered affects the relationship between interconnections and stability.

Furthermore, I split the sample between large (banks having greater than \$1 billion in GTA) and small banks (those having up to \$1 billion in GTA) and conduct the above tests for these size classes separately.

IV.3 Variables and Summary Statistics

A. Dependent Variables

I use z-score and standard deviation of ROA (return on assets) as proxies for my dependent variable, which is the stability/riskiness of a bank[12]. 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,

[12] Results are presented only for the primary dependent variable, z-score, to save space. However, results are qualitatively similar when standard deviation of ROA is used as the dependent variable.

$$z - score_i = \frac{\frac{1}{T}\sum_{\tau=0}^{T} ROA_{i,\tau} + \frac{1}{T}\sum_{\tau=0}^{T} CAR_{i,\tau}}{\sigma_0^T(ROA_i)} \tag{4}$$

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. To ensure that my results are not influenced by outliers, I winsorize all accounting variables at 1%. 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.

In addition, when I study the probit model for whether higher interconnectedness can explain high declines in stability, I construct a dummy variable identifying changes in z-score (from pre-crisis to crisis period) that is smaller than the mean for sample. This translates to any decline in the z-score value that is smaller than is -12.8%.

B. *Independent Variables*

The main independent variable that I use to capture the interconnectedness of a bank is the degree of links that a bank maintains with other banks during the pre-crisis period. Two banks are linked if they are exposed to a common local market represented by an MSA (Metropolitan Statistical Area). Specifically, if two banks originate mortgage loans for properties located in the same MSA, then I define a link between the two.

While computing the degree of links for a bank, I weight its link to another bank in the same MSA using the loan portfolio weight that it assigns to that MSA. This weight is appropriate since it captures the bank's loan exposure to the other bank. If the two banks overlap in multiple MSAs, I sum the portfolio weights for all the MSAs in which they overlap. This way, a given bank's link to another bank captures its total loan exposure to that bank. Then, the degree of links is computed by summing this weighted link over all other banks with which it is linked.

Figure 1 illustrates this computation for a hypothetical bank A, which originates loans in MSAs *i, j* and *k.* Bank B originates loans in MSA *i* and *j* while bank C originates loans in MSA *j* and *k.* The numbers along the arrows represent portfolio weights that bank A assigns to each of the MSAs. So, bank A has 30% of its loan portfolio in MSA *i*, 20% in MSA *j* and 50% in MSA *k.* As the computation below the figure shows, bank A's total loan exposure to banks B and C are 0.5 and 0.7 respectively. The degree of links for bank A is the sum of these exposures which is 1.2. This way, I first compute the degree of links for a given bank for each year during the pre-crisis period (2005 and 2006), and then take the average of these numbers to obtain a measure of average interconnectedness during the pre-crisis period.

I am also interested in mechanisms that affect the relationship between degree of links and stability. I consider as potential mechanisms, the average levels of leverage, securitization activity and liquidity ratios of other banks. First off, leverage is defined as (GTA-Equity)/GTA. Securitization refers to the fraction of total loans that a bank sells in a given year (obtained from HMDA database) 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. I construct variables that capture a bank's exposure to these mechanisms. For a given bank, I first compute the average of leverage, fraction of loans sold (securitized) and liquidity ratios of *other* banks in each of the MSAs where the bank originates loans. Then, I compute the bank's exposure to each mechanism by taking a weighted average of these values. The weights used are the portfolio weights that the bank assigns to each of these MSAs. Finally, I construct separate indicators that identify banks having above median values for each of these exposure variables.

C. Control Variables

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. Since my sample consists of bank holding companies as well as stand-alone banks, I include an indicator variable identifying bank holding company to account for any differences between them. Furthermore, I include natural logarithm of total deposits (deflated to 2009 dollars), asset quality (ratio of non-performing loans to total loans) and management quality (overhead costs/GTA).

I also control for concentration exposure of a bank to ensure that the proxy for interconnectedness is not merely capturing the effect of market concentration. To construct this variable, Herfindahl-Hirschman Index (HHI) is first computed for all MSAs in the data. HHI is measured as the sum of squares of market shares of all lenders in a given MSA and in a given year. This value ranges from zero to one – zero indicating the least concentration of lenders, and higher values indicating higher degrees of concentration. The concentration exposure of a bank is then computed by taking a weighted average of the concentration of all MSAs where the bank originates loans, and the weight assigned to each MSA is the fraction of the bank's total loan portfolio that is accounted for by the MSA.

Finally, I control for local economic conditions that can potentially affect a bank's stability. I obtain local unemployment rates for each MSA from the Bureau of Labor Statistics, and compute a given bank's exposure to local economic conditions by taking a weighted average of the unemployment rates of all MSAs where the bank originates loans. Again, the weights reflect the portfolio fractions that the bank assigns to each MSA.

Summary statistics appear in Table 1. Panel A presents summary for all of the regression variables used in the study, while Panel B compares key variables for large and small banks. Comparison of z-score levels during the crisis and pre-crisis periods indicate that large banks are, on average, riskier than small banks. Moreover, the z-score level declines during the crisis period for both size groups as expected. Also note large and small banks seem to hold similar leverage on average. But large banks are more involved in securitization activity than small banks. While large banks sell on average 34% of their mortgage loan portfolio, small banks sell 21% of their portfolio. 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).

V. EMPIRICAL RESULTS

This section discusses the main empirical results of the paper. I begin with a discussion of univariate results as a preliminary analysis of the relationship between interconnectedness and stability. Then, I present multivariate regression results on how the degree of interlinkages of a bank during the pre-crisis period affects its financial stability during the crisis period. I provide evidence that interlinkages increase distress initiated by the negative shock to the housing market in 2007. Next, I present results that underscore the role of exposure to leverage, securitization activity and liquidity holdings of other banks in a common market in amplifying or dampening the contagion effect of interconnections. For all of these tests, I present results for large and small banks separately to highlight the differences in the responses of these two categories of banks.

V.1 Univariate Results

As a preliminary analysis, I begin with a visual investigation of the relationship between degree of interconnections and stability of a bank, as measured by z-score. Figure 2 plots average z-score levels for banks having degree of interconnections (pre-crisis levels) in the following four ranges – (i) lower than mean minus 1 standard deviation (sd), (ii) greater than (mean-1sd) but lower than the mean, (iii) greater than the mean but lower than (mean+1sd) and (iv) greater than (mean+1sd). Since theory suggests that interconnectedness contributes in contagion of distress beyond a certain threshold level of the magnitude of a negative shock but offers risk diversification benefits if the shock is small enough, I contrast my graph for the crisis period (panel A) against that for the pre-crisis period (panel B). In addition to a z-score plot, panel A graphs the fraction of firms that observe the above mean decline in z-score for the given range of interconnectedness.

Panel A suggests that the z-score of a bank declines as the degree of interconnections increases. Moreover, the probability of a high decline in the z-score level increases steeply as interconnectedness increases. However, the plot in the pre-crisis period, presented in panel B, displays no clear relationship between interconnectedness and stability of a bank.

Figure 3 extends these plots by contrasting results for small and large banks, and by considering different mechanisms that potentially affect the relationship between interconnections and stability. Panel A presents average z-scores for small versus large banks having interconnections in the four different ranges mentioned above. The figure shows that as interconnectedness increases, the z-score levels decline for both sizes. Also notice that the z-score level declines at a faster rate for small banks compared to large banks.

The rest of the panels explore the mechanisms that amplify or mitigate this relationship between degree of links and z-score of a bank. Panel B contrasts average z-scores for banks having high exposure to leverage of other banks (above median exposure) with those having low exposure. Notice the decline in z-score with increasing interconnectedness is greater for banks having high exposure to leverage of other banks. This pattern is steeper for small banks than large banks. This indicates greater vulnerability of small banks to this particular mechanism. On the other hand, the relationship between interconnectedness and stability is unclear for banks having low exposure to leverage of other banks. This is true for both large and small banks.

Similarly, panel C compares z-score levels for banks with high exposure to securitization activity of other banks with those for banks with low such exposure. For large banks, the declining relationship between degree of links and z-scores appears steeper for those with high exposure to securitization activity of other banks than those with low such exposure. However, this effect is not so apparent in small banks. Given that large banks are involved in securitization activity more than small banks, it is sensible that large banks are more sensitive to exposure to securitization activities. [13]

Finally, panel D explores the effect of exposure to liquid holdings of other banks. The declining relationship between degree of links and z-scores is steeper for banks with low exposure to liquid holdings of other banks. This effect is observable in both large and small banks, although the effect seems somewhat stronger for large banks. Given that large banks hold less liquid holdings relative to small banks, it is sensible that large banks show more sensitivity to the positive effect of exposure to liquid holdings.[14]

[13, 14] See Table 1, panel B.

V.2 Interconnections and Stability

Table 2 presents estimation results for the model in equation (1). Here, I study whether degree of links maintained by banks during the pre-crisis period negatively impact their stability during the crisis period. According to Hypothesis 1, when there is a large enough negative shock, interconnections serve as channels of contagion, and hurt the stability of the financial system.

The model in panel A regresses a bank's z-score during the crisis period on the natural logarithm of the degree of links maintained by the bank during the pre-crisis period plus other control variables. Column (1) presents results for the whole sample, column (2) considers large bank (with GTA>$1 billion) subsample and column (3) considers small banks (GTA up to $1 billion). Results indicate that the degree of links of a bank is negatively related to its stability during the crisis period, and this result is statistically significant in all columns of panel A. The results also indicate that small banks are affected more than large banks although these banks were relatively more stable than large banks during the pre-crisis period (as per Table 1, panel B). This result is sensible since large banks are expected to be less vulnerable given the size and capacity advantages they have.

The results are economically significant as well. For example, consider the coefficient on *log(Degree Links)* in the first column for the whole sample. The results suggest that a standard deviation increase in the degree of links from its mean value implies a 6.8% decrease in the z-score level of a bank (or 8.4% of a standard deviation decrease from mean zscore). Alternatively, a 1% increase in the degree of links translates to approximately 0.4% decrease in the z-score of the bank. Note that the response of small banks is greater in magnitude than that of large banks. A standard deviation change in the degree of links from the mean value implies that the z-score of a large bank declines by 5.1% while that of a small bank declines by 7.5%.

Other control variables have intuitive relationships with the stability of a bank. Results for the full sample show that banks that are more stable during the pre-crisis period have greater stability during the crisis period as well. If the z-score level during the pre-crisis period was a percentage point greater, that would result in approximately half a percentage point greater z-score during the crisis period. Furthermore, higher concentration exposure and lower asset quality result in lower stability. Similarly, the significantly negative coefficient of the bank holding company indicator implies that a bank holding company is more unstable during the crisis period than an independent bank.

Panel B presents results for the probit model which tests whether interconnectedness of a bank during the pre-crisis period predicts a high decline in z-score level during the crisis period. The study of the probability of a high decline in the stability of a bank provides further perspective on the magnitude of the impact of interconnectedness.

The first regression in panel B presents coefficient values and marginal effects for the probit model estimated for the full sample. The marginal effects show that, on average, a standard deviation increase in the degree of links of a bank from its mean value results in a 3.1% increase in the probability of a high decline in the z-score. For a large bank, the increase in the probability is 3.9% while it is 3.1% for a small bank.

Overall, the results in table 3 suggest that during the crisis period, being interconnected to many other banks makes a given bank riskier, potentially amplifying the effect of the initial shock.

V.3 Mechanisms Amplifying/Mitigating the Effects of Interconnections

Next, I examine the mechanisms that amplify or mitigate the effect of interconnections documented in Section V.2. As noted earlier, I investigate exposure to average levels of leverage, securitization activity and liquid holdings of other banks as possible amplifying/mitigating mechanisms. I estimate the model in equation (3), which regresses z-score during the crisis period on degree of links, interaction between degree of links and the mechanism in consideration, plus control variables. The variable of interest in this section is the interaction term between degree of links and the contagion amplifying/mitigating mechanism.

A. Exposure to leverage of other banks in a common market

Table 3 explores exposure to average level of leverage of other banks as the potential mechanism that amplifies the costs of interconnectedness. According to hypothesis 2, the negative relationship between interconnectedness and stability of a bank should be more pronounced for banks that are exposed to higher levels of leverage of other banks.

Columns (1) through (3) present results for the regression of z-score during crisis period on interconnectedness of a bank during the pre-crisis period. Consistent with hypothesis 2, results in column (1) for the whole sample suggests that exposure to other banks having high leverage amplifies the negative relationship between interconnectedness and stability. The interaction between degree of links and dummy variable indicating high leverage exposure is negative and statistically significant for small banks. While not significant, this term is still negative for large banks. This result implies that smaller banks are the most vulnerable to this particular contagion-amplifying mechanism. Panel B of Table 1 shows that small banks and large banks have similar leverage on average (0.91 for large banks versus 0.90 for small banks).

Therefore, differences in their response to exposure to leverage of other banks are likely because small banks, due to their size and capacity limitations, are more at risk and less effective in shielding contagion effect of interconnections. The next subsection will show that exposure to securitization activity plays a more dominant role in amplifying contagion in large banks.

The impact of exposure to leverage of other banks is economically significant. For a bank that has low exposure to other leverage, column (1) in table 4 (full sample results) suggest that a one standard deviation increase in the degree of links from its mean value implies a decline of 4.3% in the z-score level (or a 5.4% of a standard deviation decline from mean zscore). On the other hand, a similar increase in degree of links of a bank with high exposure to other leverage implies twice as much decrease in its stability. In particular, it implies an 8.3% decline in z-score (or 10.4% of one standard deviation decline from mean zscore).

Columns (4) through (6) present results for the probit model in equation (2) where I explore whether leverage exposure increases the probability of a high decline in z-score of a bank. Again, the results are significant only for small banks, corroborating prior result that small banks are particularly vulnerable to this mechanism. If the degree of links increases by a standard deviation from its mean, the probability of a high decline in z-score for a small bank with low exposure to other leverage increases by 1.5%, while that for a small bank with high such exposure increases by 4.2%.

Overall, the results in table 4 provide evidence that exposure to leverage of other banks is an important mechanism that amplifies the externalities of interconnectedness in small banks.

B. Exposure to securitization activity of other banks in a common market

Next, table 4 considers exposure to average securitization activity of other banks as another mechanism that potentially accelerates the transmission of distress through interlinkages. According to hypothesis 3, the negative impact of interconnections on the stability of a bank during the crisis period should be more pronounced for banks that are exposed to higher levels of securitization.

Results in table 4 suggest exposure to securitization activity of other banks is an important contagion-amplifying mechanism for large banks. The interaction between degree of links and securitization exposure is not significant for small banks. Panel B of Table 1 reveals that large banks are involved in securitization activity more than small banks. They sold 34% of their loan portfolio during the pre-crisis period, while small banks sold 21% of their loans. This difference is statistically significant as well. This should imply that when the securitization market froze during the crisis period, large banks were forced to hold greater fraction of their loans that they intended to sell. To the extent that the loans meant for sale are of poorer quality, large banks should be affected more when the securitization market freezes. Moreover, areas with high levels of securitization activity should face greater difficulty in selling loans. Therefore, it is sensible that large banks show greater vulnerability to exposure to securitization than smaller banks.

The second column for the large bank subsample indicates that exposure to securitization activity of other banks is an economically significant mechanism that amplifies the externalities of interconnections. Specifically, a standard deviation increase in a large bank's degree of links from its mean value decreases z-score by 15.2% (or 20.8% of one standard deviation decrease from mean-zscore).[15] On the other hand, the relationship between degree of links and z-score is not statistically significant for a large bank having low exposure to other securitization.

Columns (4) through (6) consider the impact of degree of links on the probability of a high decline in z-score of a bank. Again, results are significant only for the large bank subsample. Analysis of marginal effects for results in Column (5) suggests that a standard deviation increase in degree links from the mean value results in a 8.2% increase in the probability of a high decline in z-score for a large bank with high exposure to other securitization, while the probability only increases by 2.4% for a large bank with low such exposure.

Overall, the results in table 4 suggest that the level of securitization activity of other banks is an important mechanism that amplifies the negative relationship between interconnectedness and stability of large banks.

C. Exposure to liquid holdings of other banks in a common market

Finally, table 5 considers the mitigating impact of exposure to aggregate liquid holdings of other banks on the relationship between interconnections and bank stability. According to hypothesis 4, the magnitude of the negative effect of interconnections on a bank's stability should be less for those that are exposed to higher levels of liquid holdings of other banks than those that have less such exposure.

Results in table 5 are consistent with the hypothesis, and the effect of this mechanism is significant for both large and small banks. Moreover, the impact of this mechanism is of greater magnitude relative to other mechanisms considered above. Column (1) (full sample results)

[15] In column (2), table 5, the sum of coefficients for *log(Degree Links)* and the interaction term between degree links and dummy identifying high exposure to other securitization is statistically different from zero.

suggests that the magnitude of the negative relationship between degree of links and stability is smaller for banks having high exposure to liquid holdings of other banks than those that have low such exposure. Large banks show greater sensitivity to this channel than small banks. Again, if we study panel B of Table 1, the summary statistics indicate that large banks carried smaller liquid holdings in their portfolio during the pre-crisis period than small banks (18% for large banks versus 26% for small banks), and this difference is statistically significant. Therefore, it can be argued that large banks are more sensitive to run risk and fire-sale spillover effects in the event of a negative shock. Furthermore, the sensitivity should be greater in areas with lower levels of liquid holdings of other banks. Therefore, it is sensible that the results show greater sensitivity of large banks to this mechanism.

Again, these results are economically significant. The first column for the full sample indicates that for a bank with low exposure to liquid holdings of other banks, a standard deviation increase in degree of links from its mean value implies a 15.8% decrease in z-score of the bank (or a 19.6% of a standard deviation decrease from mean-zscore). On the other hand, a bank with high such exposure faces only a 5.1% decline in z-score (or a 6.3% of a standard deviation decrease from mean-zscore).

Columns (4) through (6) present results for the probit model, in which the dependent variable is the indicator for a high decline in z-score level of a bank. Results suggest that exposure to liquid holdings of other banks mitigates the probability of a high decline in z-score due to high interconnectedness for large and small banks alike. The analysis of the marginal effects reveals that for an average bank (using column (4)) with low exposure to liquid holdings of other banks, a standard deviation increase in degree of links from the mean value implies a 7%

increase in the probability of a high decline in z-score, while for a bank with high such exposure, it implies a decrease of 1.6% only.

Overall, the results in table 5 provide evidence that increased liquid holdings of banks help mitigate the contagion effect of interconnections. This effect is statistically and economically significant for both large and small banks.

V.4 Robustness tests

A. Placebo test

In this section, I investigate whether interconnections served as channels for contagion only in response to the housing market shock of 2007 or if the documented results hold during normal times as well. As mentioned before, theory suggests that interconnections facilitate contagion only during bad times. In order to test this, I run the same analysis as before using a "fake" crisis period of 2005-2006. For this crisis period, I label 2003-2004 as the relevant pre-crisis period. If the negative relationship between degree of links and financial stability documented in the previous subsections is a result of the negative shock, then such effect should not be apparent in this placebo test.

Table 6 presents estimation results for equations (1) and (2) around the fake crisis period. Panel A results show that interconnectedness of a bank is, on average, negatively related to its z-score during the fake crisis period. However, the coefficients are an order magnitude smaller than the ones obtained in the regressions performed for the real crisis scenario. While a standard deviation increase in the degree of links from its mean value implied a decrease of 7.5% in the z-score of a small bank during the real crisis period, it now implies a decrease of only 0.3%. Moreover, the effect of interconnections is no longer significant for the large bank subsample.

Panel B considers the probability of a high decline in z-score during the fake crisis period. The results are statistically insignificant for both large and small banks. Thus, there is no evidence that interconnectedness increases the probability of a high decline in stability during normal times.

Table 7 presents estimation results for model (3) in which I study the contagion-magnifying/mitigating effect of exposure to leverage, securitization activity and liquid holdings of other banks. The table presents results for the full sample.[16] Again, none of the interaction terms of interest are statistically significant.

Overall, results of the placebo test do not provide any evidence of the costs associated with the contagion effect of interbank linkages during normal times. The results pertaining to the analysis around the 2007 financial crisis seem to be a result of the contagion effect of interconnections triggered by the large negative shock to the housing market.

B. Exclusion of the top bubble markets

In this subsection, I confirm that my results are not being driven by banks in only a few bubble markets. To this end, I obtain house price index (HPI) (traditional, all-transactions index) provided by the FHFA at the MSA level and for the end of the years 2004 and 2006.[17] I identify MSAs that observe the top 1 percentile increase in the HPI from the end of 2004 to 2006. This corresponds to MSAs where the HPI levels increase by greater than or equal to 148% from the end of 2004 to the end of 2006. [18] Then, I obtain a subsample of lenders that do not originate

[16] I present estimation results only for the full sample to conserve space. Results for large and small bank subsamples are qualitatively similar.
[17] HPI Index available at https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx#atvol.
[18] These MSAs include Bend-Redmond (OR), Phoenix-Mesa-Scottsdale (AZ) and St. George (UT).

mortgages in these MSAs during the pre-crisis period. This subsample contains 1168 lenders, and I perform tests similar to the prior ones in this subsample.

Table 8 presents the results. Prior results on the relationship between interconnections and stability as well as the mechanisms that affect this relation hold in this subsample. Panel A presents results for large banks. They show that having high degree of interconnections increases the probability of a high decline in stability. Moreover, exposure to high securitization activity of other banks worsens this negative impact of interconnections on stability, whereas exposure to high liquid holdings of other banks mitigates this negative effect. Similarly, Panel B presents results for small banks. Again, the results show a negative relationship between connectedness and stability for these banks, and this effect is greater than that for large banks. As before, exposure to leverage of other banks plays a more dominant role in amplifying the negative impact of interconnections for small banks, and exposure to high liquid holdings of other banks helps mitigate the negative effect.

C. Public bank subsample

Next, I perform my analysis in a subsample of public banks. This allows me to use measures based on market data, and most importantly, it facilitates the study of idiosyncratic risk of a bank separately from its systematic risk as explained below. While limiting my sample to the public subsample reduces sample size, this test provides further evidence of the implications of interconnectedness of a bank on its risk that is not simply driven by overall market risk.

First, using the CRSP-FRB Link provided by the Federal Reserve Bank of New York, I identify public banks, and use the identifiers provided in the link table to obtain stock price data from CRSP (Center for Research In Security prices) available through WRDS. The first measure for bank risk I use is the overall market risk of each bank calculated as the standard deviation of weekly market returns in a given year. 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 bank risk – 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:

$$r_{i,t} = \alpha_i + \beta_{1,i}\, r_{m,t} + \beta_{2,i}\, (Baa - Aaa)_t + \beta_{3,i}\, (3 - month\, T - bill)_t + \epsilon_{i,t} \tag{5}$$

where $r_{m,t}$ is the weekly return of the S&P 500 index, $(Baa - Aaa)_t$ is the default risk factor computed as the difference between yields on a *Baa* and *Aaa* rated corporate bonds, and $(3 - month\, T - bill)_t$ is the interest risk factor computed as the change in the yield of a 3-month treasury bill. Data for these variables are obtained from the Federal Reserve Economic Data provided by the Federal Reserve Bank of St. Louis. I run the regression in equation (6) for each bank *i* separately, and collect residuals from each of the regressions. The standard deviation of these residuals represents the idiosyncratic risk of a bank, and I use this as my second measure for bank risk.

Table 9 presents results for the estimation of equations (1) and (3). Columns (1) and (5) corroborate prior results that interconnectedness increases instability of a bank. Specifically, the degree of linkages of a bank increases the overall market return risk of the bank. Moreover, focusing on the idiosyncratic part of the market risk does not change this result. Columns (2) and (6) explore exposure to leverage of other banks as a potential contagion-amplifying mechanism. However, the interaction term of interest here is not significant. The majority of the public bank subsample constitutes large banks, and this result is actually consistent with prior results which show that leverage exposure does not play a dominant role in magnifying the externalities of interconnections in large banks. Columns (3) and (7) show that high exposure to securitization activity of other banks magnifies the negative impact of degree links on overall market risk as well as idiosyncratic risk, while columns (4) and (8) show that high exposure to liquid holdings of other banks mitigates this impact.

VI. CONCLUSION

The 2007 financial crisis heightened the need for a better understanding of how the network structure of a financial system affects its stability. Moreover, empirical work has not yet produced a convincing link between interconnectedness and stability of the financial system (Glasserman and Young (2015)). This paper addresses this need by conducting an empirical study of the relationship between a bank's degree of links and its stability. Using detailed home mortgage loan data, I consider linkages formed between banks due to exposure to common local housing markets, and study the role of a bank's interconnectedness during the pre-crisis period in explaining their stability during the crisis period. I find that interconnections of banks serve as means of contagion of distress initiated by the negative shock to the housing market in 2007. While small banks (having GTA up to $1 billion) are, in particular, more vulnerable to such spillover effects, further tests show that there exist mechanisms that amplify the contagion effect of interlinks, and even large banks (with GTA>$1 billion) are susceptible to these vulnerabilities.

I investigate exposure to average levels of leverage, securitization activity and liquid holdings of other banks as mechanisms that affect the relationship between interconnectedness and stability. I investigate large and small banks separately to study their differential responses to these mechanisms. Results show that exposure to leverage and securitization activities of other banks amplifies the costs of interlinkages; exposure to leverage plays a dominant role in small banks, while exposure to securitization plays a greater role in large banks. On the other hand, being exposed to higher levels of liquid holdings of other banks dampens the costs of interconnections. Importantly, this effect is significant for both large and small banks.

Moreover, the results discussed do not hold when I conduct a placebo test using a “fake” crisis period. This suggests that interconnectedness poses a risk to financial stability when there is a large negative shock to the financial system and that the costs of interconnections are not high during normal times.

These results provide important policy implications by identifying mechanisms that amplify and mitigate the costs of interconnections and also by suggesting which classes of banks are affected the most by each of these mechanisms. The result that liquid holdings of banks help reduce the externalities of interconnections is especially interesting. The issue of whether banks should hold more liquid assets has received much attention since the financial crisis, and new liquidity requirements were recently introduced in order to ensure that banks maintain enough buffers to absorb losses and stand run risks when a negative shock hits. Results of this paper are encouraging from a regulator’s perspective in that they suggest higher levels of liquid holdings of banks help dampen contagion effect of interbank linkages, and thus improve the health of the financial system.

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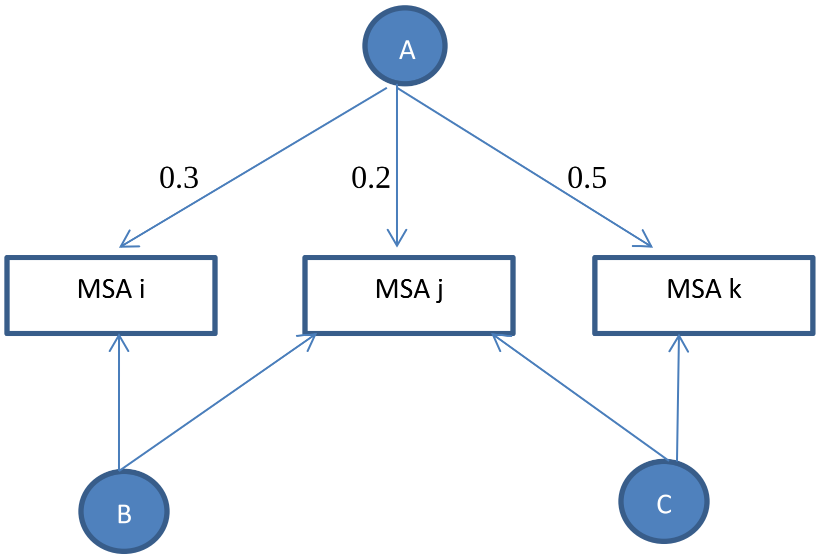
Figure 1: Degree of Links Definition

This figure illustrates the computation of degree of links for a hypothetical bank A, which is linked to banks B and C through MSAs (Metropolitan Statistical Area) *i*, *j* or *k*. Each arrow indicates that the bank originates loans in the given MSA. The numbers against the arrows are the portfolio weights that bank A assigns to each MSA. The computation below the figure illustrates how degree of links is constructed for bank A.



Loan exposure of bank A to

bank B: 0.3 + 0.2 = 0.5

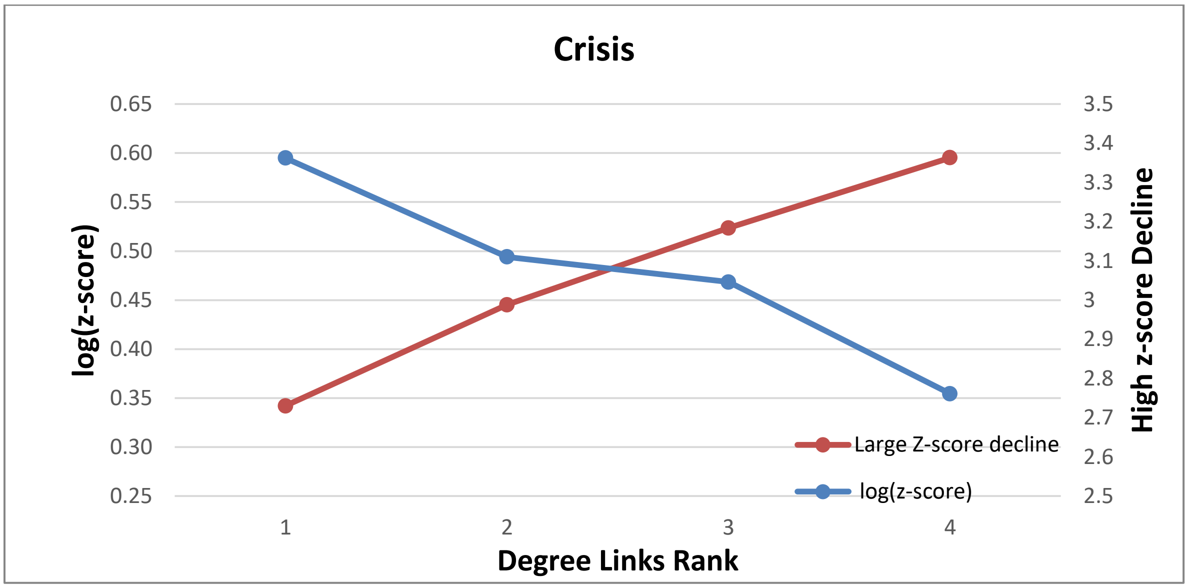
bank C: 0.5 + 0.2 = 0.7

Bank A's degree of links = 0.5 + 0.7 = 1.2

Figure 2: Z-scores and Interconnections around 2007 Financial Crisis

This figure plots the relationship between z-scores and interconnectedness prior to and during the crisis period. Panel A plots average z-score levels (logged values) and percentage of firms with high declines in z-scores during the crisis period against interconnectedness measured during the pre-crisis period. *Degree Links Rank* takes four values – 1 refers to log(degree links)≤(mean-1sd), 2 refers to log(degree links) in (mean-1sd, mean], 3 refers to log(degree links) in (mean, mean+1sd] and 4 refers to log(degree links)≥(mean+1sd). A bank experiences a high decline in z-score if its percent change in z-score from the pre-crisis to the crisis period is smaller than the mean for the sample. Panel B plots pre-crisis levels of z-scores (logged values) against *Degree Links Rank* measured during the pre-crisis period. Crisis period includes years 2007-2009 while the pre-crisis period includes years 2005-2006.

Panel A



Panel B

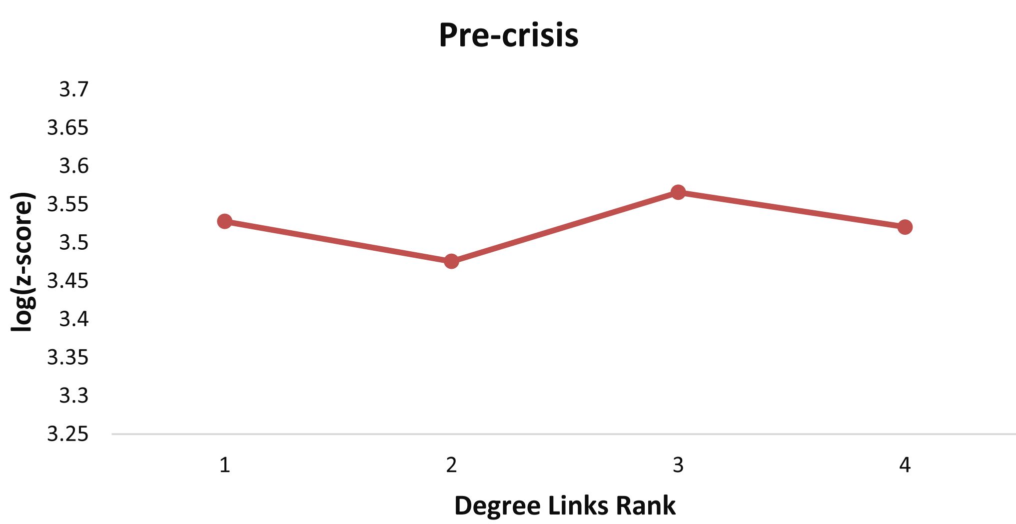
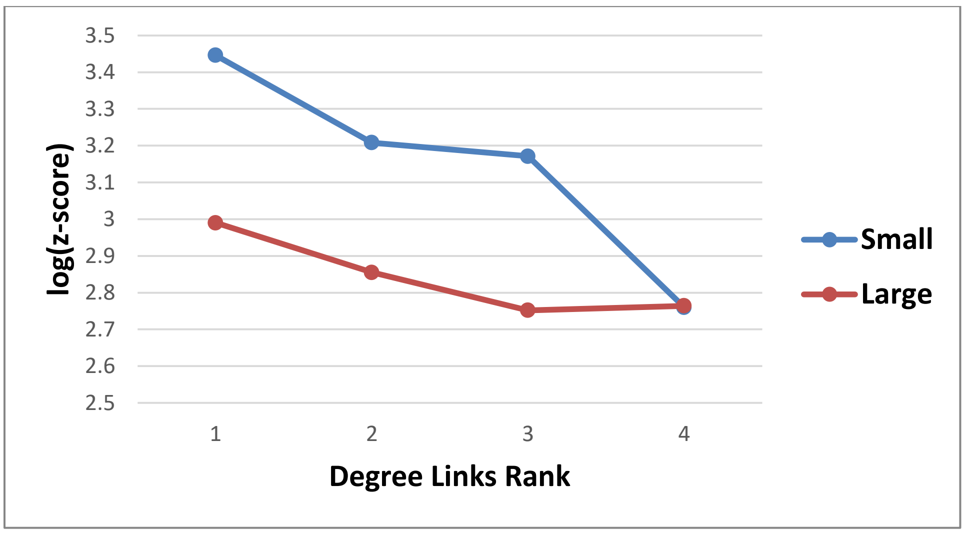


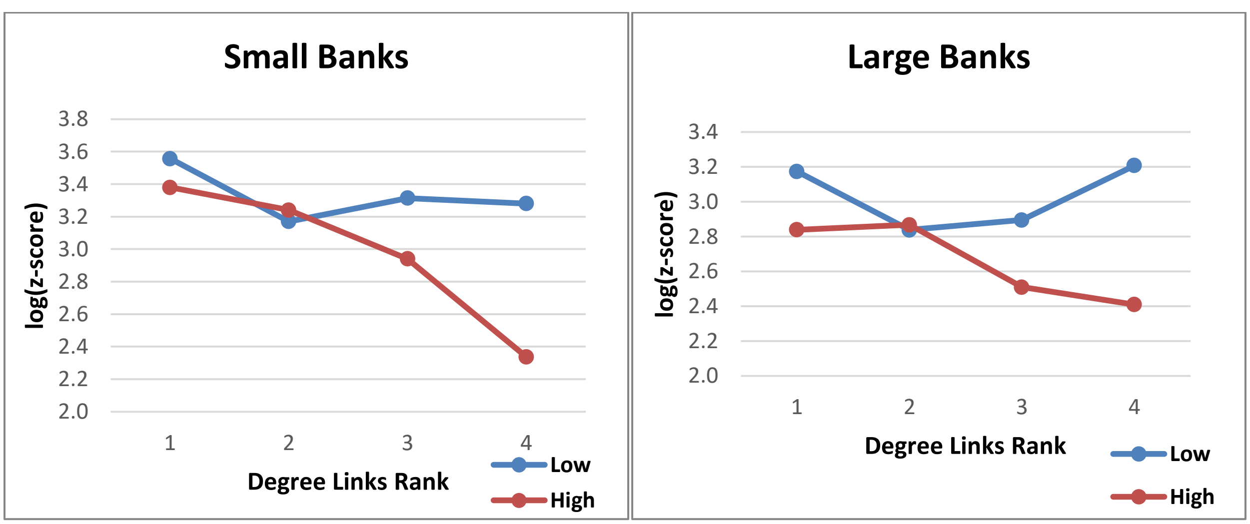
Figure 3: Amplifying Mechanisms

This figure plots the relationship between interconnections and stability (as measured by log(z-score)) for small (<$1 billion in gross assets) and large banks (upto $1 billion in gross assets) separately, and explores different mechanisms amplifying this relationship. It plots average z-score levels (logged values) against interconnections. *Degree Links Rank* takes four values – 1 refers to log(degree links)≤(mean-1sd), 2 refers to log(degree links) in (mean-1sd, mean], 3 refers to log(degree links) in (mean, mean+1sd] and 4 refers to log(degree links)≥(mean+1sd). Panel A shows how the relationship between degree links and z-score differs in small versus large banks. Panel B displays how the relationship varies in banks having low versus high exposure to leverage of other banks. Panel C considers banks having low versus high exposure to securitization activity of other banks, while panel D considers banks having low versus high exposure to liquid holdings of other banks.

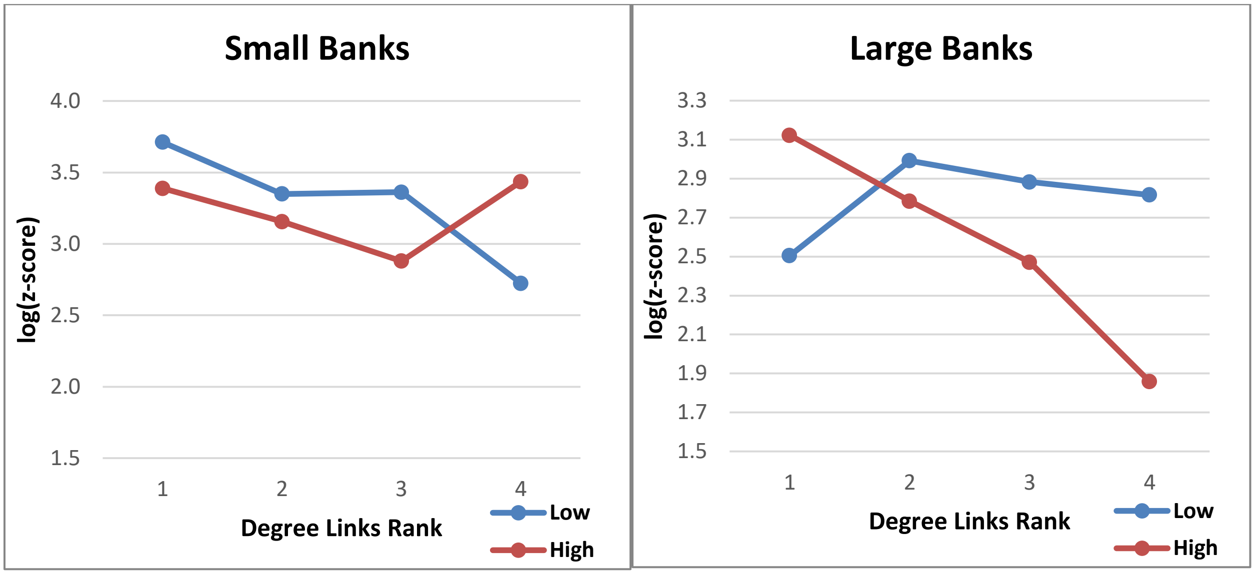
Panel A: Degree of links and Stability



Panel B: Exposure to Other Leverage



Panel C: Exposure to Other Securitization



Panel D: Exposure to Other Liquid Holdings

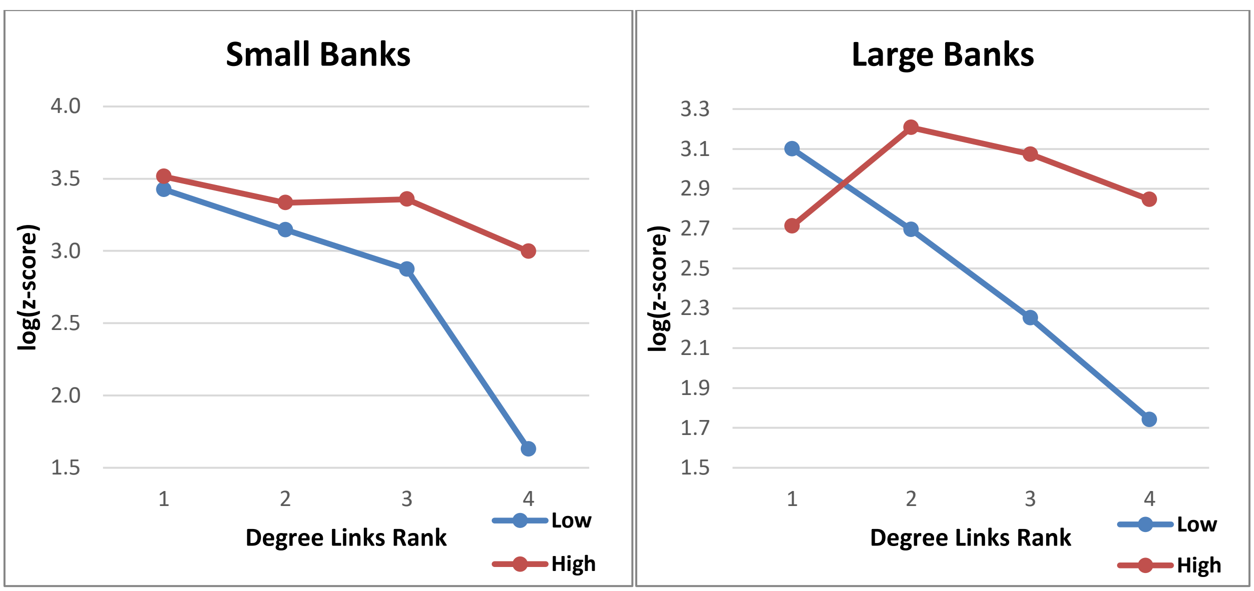


Table 1: Summary Statistics

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

Panel A

Variable	N	Mean	SD	Min	5 pct	Median	95 pct	Max
Dependent Variable								
log(crisis Zscore)	1348	3.07	0.99	0.28	1.05	3.3	4.43	4.87
Independent Variable								
Degree Links	1348	56.93	27.15	5.98	22.42	53.63	104.88	144.5
log(Degree Links)	1348	3.93	0.5	1.79	3.11	3.98	4.65	4.97
Control Variables								
log(pre-crisis Zscore)	1348	3.53	0.5	2.31	2.75	3.47	4.45	4.88
Concentration Exposure	1348	0.14	0.05	0.07	0.09	0.13	0.21	0.55
Unemployment Exposure	1348	4.8	1.06	2.65	3.32	4.77	6.46	15.45
log(deposits)	1348	12.98	1.36	10.51	10.85	12.99	15.43	17.68
Asset Quality	1348	0.01	0.01	0	0	0	0.02	0.04
Management Quality	1348	0.02	0.01	0.01	0.01	0.02	0.03	0.04

Panel B

	Small			Large			Small-Large
	N	Mean	Std. Dev	N	Mean	Std. Dev	Difference in Means
log(crisis Zscore)	989	3.17	0.98	359	2.81	1.00	.35***
log(pre-crisis Zscore)	989	3.58	0.54	359	3.38	0.37	.20***
log(Degree Links)	989	3.91	0.50	359	3.97	0.49	-.06 ***
Degree Links	989	56.27	27.35	359	58.75	26.52	-2.48
Fraction of Loans Sold	989	0.21	0.29	359	0.34	0.29	-0.13***
Leverage	989	0.90	0.03	359	0.91	0.03	-.01***
Liquidity Ratio	989	0.26	0.16	359	0.18	0.12	.09***

Table 2: Z-scores and Interconnectedness

This table shows how degree of links during the pre-crisis period (2005-2006) affects stability during the crisis period (2007-2009). Panel A reports OLS regression estimates for equation (1), in which the dependent variable used is *log(z-score)* during the crisis period. Panel B reports 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 period is smaller than the mean for the sample). The main independent variable in both models is *log(Degree links)*, which is computed as natural logarithm of the weighted degree of interconnections. Columns 1, 2 and 3 for both panels present results for the full sample, large bank subsample (>$1bill GTA), and small bank subsample (up to $1bill GTA) respectively. 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)		
	(1)	(2)	(3)
	Full Sample	Large	Small
log(Degree Links)	-0.387***	-0.309**	-0.420***
	(0.053)	(0.120)	(0.059)
log(pre-crisis Zscore)	0.541***	0.449***	0.552***
	(0.060)	(0.172)	(0.064)
Concentration Exposure	-1.527***	-0.888	-1.356**
	(0.519)	(1.271)	(0.558)
Unemployment exposure	-0.026	-0.098**	0.023
	(0.024)	(0.044)	(0.025)
log(Deposits)	-0.003	0.031	-0.007
	(0.024)	(0.045)	(0.044)
BHC	-0.404***	-0.388**	-0.382***
	(0.070)	(0.189)	(0.084)
Asset Quality	-9.288***	-24.644**	-6.512*
	(3.268)	(9.567)	(3.436)
Management Quality	-2.627	11.401	-9.195*
	(4.508)	(9.513)	(5.266)
Constant	3.411***	2.985**	3.395***
	(0.462)	(1.165)	(0.686)
Observations	1,348	359	989
R-squared	0.194	0.095	0.221

Panel B

	Pr(High Z-score Decline)					
	(1)		(2)		(3)	
	Full Sample		Large		Small	
	Coeff	Marginal Effect	Coeff	Marginal Effect	Coeff	Marginal Effect
log(Degree Links)	0.465***	0.185***	0.603***	0.241**	0.453***	0.180***
	(0.080)	(0.032)	(0.184)	(0.073)	(0.090)	(0.036)
log(pre-crisis Zscore)	0.564***	0.225***	0.661***	0.264**	0.564***	0.224***
	(0.079)	(0.031)	(0.206)	(0.082)	(0.086)	(0.034)
Concentration Exposure	0.961	0.383	0.521	0.208	0.727	0.289
	(0.811)	(0.323)	(1.841)	(0.734)	(0.914)	(0.363)
Unemployment exposure	0.051	0.020	0.207***	0.082**	-0.026	-0.010
	(0.035)	(0.014)	(0.067)	(0.027)	(0.041)	(0.016)
log(Deposits)	-0.026	-0.010	-0.031	-0.012	-0.023	-0.009
	(0.034)	(0.014)	(0.067)	(0.027)	(0.071)	(0.028)
BHC	0.508***	0.202***	0.677**	0.270*	0.481***	0.192***
	(0.099)	(0.039)	(0.264)	(0.105)	(0.127)	(0.050)
Asset Quality	13.024***	5.189**	34.853***	13.902**	9.195*	3.658
	(5.048)	(2.011)	(12.900)	(5.146)	(5.427)	(2.159)
Management Quality	-0.832	-0.331	-20.490*	-8.173	7.320	2.912
	(6.105)	(2.432)	(12.425)	(4.956)	(7.273)	(2.893)
Constant	-4.280***		-5.716***		-3.976***	
	(0.678)		(1.607)		(1.074)	
Observations	1,348		359		989	
Pseudo R2	0.0563		0.0788		0.0601	

Table 3: Amplifying Mechanism: Exposure to Leverage of Other Banks

This table shows how exposure to leverage of other banks affects the implications of degree of links during the pre-crisis period (2005-2006) on stability during the crisis period (2007-2009). Columns (1) through (3) report OLS regression estimates for equation (1), in which the dependent variable used is *log(z-score)* during the crisis period. Columns (4) through (5) 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 period is smaller than the mean 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 *log(Degree links)*, which is computed as the natural logarithm of the weighted degree of interconnections. *Dummy High Other Leverage* is an indicator identifying banks with above median exposure to average leverage of other banks in markets where the bank originates loans. 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)			Pr(High Z-score Decline)		
	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample	Large	Small	Full Sample	Large	Small
log(Degree Links)	-0.249***	-0.205	-0.224***	0.272**	0.298	0.224*
	(0.077)	(0.181)	(0.084)	(0.119)	(0.260)	(0.134)
log(Degree Links) * Dummy High Other Leverage	-0.224**	-0.153	-0.328***	0.320**	0.511	0.390**
	(0.099)	(0.216)	(0.111)	(0.153)	(0.333)	(0.176)
Dummy High Other Leverage	0.733*	0.438	1.118***	-1.087*	-1.872	-1.326*
	(0.380)	(0.855)	(0.416)	(0.604)	(1.327)	(0.691)
Controls	Y	Y	Y	Y	Y	Y
Observations	1,348	359	989	1,348	359	989
R-squared	0.202	0.103	0.234			
Pseudo R2				0.0618	0.0864	0.0678

Table 4: Amplifying Mechanism: Exposure to Securitization Activity of Other Banks

This table shows how exposure to securitization activity of other banks affects the implications of degree of links during the pre-crisis period (2005-2006) on stability during the crisis period (2007-2009). Columns (1) through (3) report OLS regression estimates for equation (1), in which the dependent variable used is *log(z-score)* during the crisis period. Columns (4) through (5) 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 period is smaller than the mean 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 *log(Degree links)*, which is computed as the natural logarithm of the weighted degree of interconnections. *Dummy High Other Securitization* is an indicator identifying banks with above median exposure to average securitization of other banks in markets where the bank originates loans. 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)			Pr(High Z-score Decline)		
	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample	Large	Small	Full Sample	Large	Small
log(Degree Links)	-0.350***	-0.198	-0.511***	0.324***	0.373*	0.433***
	(0.079)	(0.139)	(0.090)	(0.115)	(0.227)	(0.144)
log(Degree Links) * Dummy High Other Securitization	-0.175	-0.676***	0.097	0.369**	0.932**	0.107
	(0.110)	(0.247)	(0.122)	(0.170)	(0.377)	(0.201)
Dummy High Other Securitization	0.594	2.369**	-0.472	-1.400**	-3.459**	-0.353
	(0.427)	(0.943)	(0.468)	(0.670)	(1.466)	(0.798)
Controls	Y	Y	Y	Y	Y	Y
Observations	1,348	359	989	1,348	359	989
R-squared	0.197	0.124	0.223			
Pseudo R2				0.0590	0.0933	0.0607

Table 5: Mitigating Mechanism: Exposure to Liquid Holdings of Other Banks

This table shows how exposure to liquid holdings of other banks affects the implications of degree of links during the pre-crisis period (2005-2006) on stability during the crisis period (2007-2009). Columns (1) through (3) report OLS regression estimates for equation (1), in which the dependent variable used is *log(z-score)* during the crisis period. Columns (4) through (5) 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 period is smaller than the mean 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 *log(Degree links)*, which is computed as the natural logarithm of the weighted degree of interconnections. *Dummy High Other Liquidity* is an indicator identifying banks with above median exposure to average liquid holdings of other banks in markets where the bank originates loans. 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)			Pr(High Z-score Decline)		
	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample	Large	Small	Full Sample	Large	Small
log(Degree Links)	-0.864***	-1.061***	-0.786***	1.055***	1.719***	0.893***
	(0.084)	(0.211)	(0.094)	(0.131)	(0.324)	(0.143)
log(Degree Links) * Dummy High Other Liquidity	0.573***	0.764***	0.439***	-0.822***	-1.351***	-0.630***
	(0.103)	(0.231)	(0.114)	(0.163)	(0.365)	(0.188)
Dummy High Other Liquidity	-1.878***	-2.384***	-1.402***	2.966***	4.828***	2.243***
	(0.387)	(0.877)	(0.424)	(0.640)	(1.425)	(0.741)
Controls	Y	Y	Y	Y	Y	Y
Observations	1,348	359	989	1,348	359	989
R-squared	0.236	0.192	0.251			
Pseudo R2				0.0749	0.122	0.0722

Table 6: Z-scores and Interconnectedness (Placebo Test)
This table studies the relationship between degree of links and stability around the "fake" crisis period ("fake" crisis: 2005-2006, "fake" pre-crisis: 2003-2004).). Panel A reports OLS regression estimates for equation (1), in which the dependent variable used is *log(z-score)* during the crisis period. Panel B reports 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 period is smaller than the mean for the sample). The main independent variable in both models is *log(Degree links),* which is computed as natural logarithm of the weighted degree of interconnections. Columns 1, 2 and 3 for both panels present results for the full sample, large bank subsample (>$1bill GTA), and small bank subsample (up to $1bill GTA) respectively. 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)		
	(1)	(2)	(3)
	Full Sample	Large	Small
log(Links)	-0.045***	-0.030	-0.051***
	(0.015)	(0.028)	(0.017)
log(pre-crisis Zscore)	0.670***	0.622***	0.673***
	(0.026)	(0.072)	(0.027)
Concentration Exposure	-0.780***	-0.758***	-0.785***
	(0.134)	(0.210)	(0.156)
Unemployment exposure	0.004	0.003	0.009
	(0.008)	(0.012)	(0.010)
log(Deposits)	0.010	-0.000	0.013
	(0.007)	(0.015)	(0.017)
BHC	-0.179***	-0.255***	-0.174***
	(0.022)	(0.055)	(0.025)
Asset Quality	3.427**	-4.375	4.770***
	(1.332)	(3.367)	(1.438)
Management Quality	-1.761	-3.648	-0.988
	(1.433)	(3.276)	(1.623)
Constant	1.427***	1.852***	1.346***
	(0.170)	(0.376)	(0.266)
Observations	2,029	380	1,649
R-squared	0.479	0.502	0.475

Panel B

	Pr(High Z-score Decline)					
	(1)		(2)		(3)	
	Full Sample		Large		Small	
	Coeff	Marginal Effect	Coeff	Marginal Effect	Coeff	Marginal Effect
log(Degree Links)	-0.013	-0.005	0.048	0.018	-0.024	-0.009
	(0.055)	-0.02	(0.143)	-0.054	(0.060)	-0.022
log(pre-crisis Zscore)	0.510***	0.188	0.906***	0.344	0.468***	0.172
	(0.071)	-0.026	(0.225)	-0.085	(0.074)	-0.027
Concentration Exposure	1.710***	0.632	2.390*	0.907	1.641***	0.602
	(0.542)	-0.2	(1.336)	-0.507	(0.599)	-0.219
Unemployment exposure	-0.010	-0.004	-0.021	-0.008	-0.006	-0.002
	(0.029)	-0.011	(0.057)	-0.022	(0.034)	-0.012
log(Deposits)	-0.065**	-0.024	-0.012	-0.005	-0.081	-0.03
	(0.028)	-0.01	(0.069)	-0.026	(0.058)	-0.021
BHC	0.565***	0.209	0.877***	0.333	0.548***	0.201
	(0.073)	-0.027	(0.223)	-0.085	(0.085)	-0.031
Asset Quality	-10.459***	-3.864	0.389	0.148	-12.141***	-4.453
	(3.304)	-1.221	(8.660)	-3.287	(3.594)	-1.318
Management Quality	6.305	2.329	13.417	5.092	3.594	1.318
	(4.600)	-1.699	(10.692)	-4.058	(5.202)	-1.908
Constant	-1.128**		-4.013**		-0.670	
	(0.551)		(1.563)		(0.857)	
Observations	2,029		380		1,649	
Pseudo R2	0.0440		0.0570		0.0435	

Table 7: Exposure to Leverage, Securitization activity and Liquid Holdings of Other Banks (Placebo Test)

This table presents the impact of exposure to leverage, securitization activity and liquid holdings of other banks on the relationship between degree of links and stability around the "fake" crisis period ("fake" crisis: 2005-2006, "fake" pre-crisis: 2003-2004). Columns (1) and (2) study exposure to leverage, (3) and (4) study exposure to securitization activity, while (5) and (6) study exposure to liquid holdings. For each mechanism, I report estimation results for the OLS regression in equation (1) and the probit model in equation (2). The OLS regression uses crisis (fake) *log(z-score)* as the dependent variable, while the probit model uses an indicator variable identifying high decline in z-score (%change in z-score from pre-crisis to crisis period is smaller than the mean for the sample) as the dependent variable. The main independent variable in both models is *log(Degree links)*, which is computed as the natural logarithm of the weighted degree of interconnections. Results are presented for the full sample only. *Dummy High Other Leverage* is an indicator identifying banks with above median exposure to average leverage of other banks in markets where the bank originates loans. *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.

	(1) log(crisis Z-score)	(1) Pr(High Z-score Decline)	(1) log(crisis Z-score)	(1) Pr(High Z-score Decline)	(1) log(crisis Z-score)	(1) Pr(High Z-score Decline)
log(Degree Links)	-0.055**	-0.056	-0.039*	-0.014	-0.088***	-0.056
	(0.028)	(0.100)	(0.022)	(0.078)	(0.022)	(0.100)
log(Degree Links) * Dummy High Other Leverage	0.007	0.086				
	(0.032)	(0.116)				
Dummy High Other Leverage	-0.085	-0.145				
	(0.132)	(0.484)				
log(Degree Links) * Dummy High Other Securitization			-0.007	0.017		
			(0.030)	(0.117)		
Dummy High Other Securitization			0.039	-0.050		
			(0.124)	(0.485)		
log(Degree Links) * Dummy High Other Liquidity					0.046	0.086
					(0.031)	(0.116)
Dummy High Other Liquidity					-0.142	-0.145
					(0.126)	(0.484)
Controls	Y	Y	Y	Y	Y	Y
Observations	2,029	2,029	2,029	2,029	2,029	2,029
R-squared	0.482		0.479		0.481	
Pseudo R2		0.0487		0.0440		0.0487

Table 8: Exclusion of the top bubble markets

This table presents results for the relationship between interconnectedness and stability around the 2007 crisis for the subsample of banks that do not originate mortgages in the MSAs that observe the top 1 percentile increase in the house price index (HPI) levels from the end of 2004 to the end of 2006. It also presents results on mechanisms that magnify/mitigate this relationship. Panel A reports results for large banks (>$1bill GTA), while panel B reports results for small banks (up to $1bill GTA). Each panel presents OLS regression estimates for equation (1) and probit model results for equation (2). The OLS regression uses crisis *log(z-score)* as the dependent variable, while the probit model uses an indicator variable identifying a high decline in z-score (%change in z-score from pre-crisis to crisis period is smaller than the mean for the sample) as the dependent variable. The main independent variable in both models is *log(Degree links)*, which is computed as the natural logarithm of the weighted degree of interconnections. *Dummy High Other Leverage* is an indicator identifying banks with above median exposure to average leverage of other banks in markets where the bank originates loans. *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.

Panel A

	Large Banks							
	log(crisis Z-score)				Pr(High z-score Decline)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Degree Links)	-0.151	-0.064	-0.036	-0.705***	0.497**	0.205	0.237	1.427***
	(0.135)	(0.182)	(0.151)	(0.270)	(0.227)	(0.296)	(0.261)	(0.432)
log(Links) * Dummy High Other Leverage		-0.170				0.651		
		(0.225)				(0.423)		
Dummy High Other Leverage		0.248				-2.080		
		(0.889)				(1.662)		
log(Links) * Dummy High Other Securitization			-0.601**				0.932**	
			(0.288)				(0.473)	
Dummy High Other Securitization			2.201**				-3.590**	
			(1.066)				(1.808)	
log(Links) * Dummy High Other Liquidity				0.503*				-1.091**
				(0.291)				(0.467)
Dummy High Other Liquidity				-1.494				3.898**
				(1.075)				(1.783)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	237	237	237	237	237	237	237	237
R-squared	0.138	0.184	0.153	0.187				
Pseudo R2					0.0925	0.121	0.103	0.114

Panel B

	Small Banks							
	log(crisis Z-score)				Pr(High z-score Decline)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Degree Links)	-0.410***	-0.234***	-0.498***	-0.788***	0.449***	0.267*	0.417***	0.924***
	(0.061)	(0.085)	(0.092)	(0.096)	(0.093)	(0.138)	(0.146)	(0.149)
log(Degree Links) * Dummy High Other Leverage		-0.304***				0.321*		
		(0.114)				(0.182)		
Dummy High Other Leverage		1.008**				-1.054		
		(0.426)				(0.713)		
log(Links) * Dummy High Other Securitization			0.108				0.111	
			(0.125)				(0.207)	
Dummy High Other Securitization			-0.501				-0.391	
			(0.478)				(0.820)	
log(Links) * Dummy High Other Liquidity				0.468***				-0.698***
				(0.117)				(0.194)
Dummy High Other Liquidity				-1.511***				2.506***
				(0.432)				(0.763)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	931	931	931	931	931	931	931	931
R-squared	0.214	0.228	0.216	0.246				
Pseudo R2					0.0600	0.0665	0.0604	0.0739

Table 9: Public Bank Subsample

This table presents results for the relationship between interconnectedness and stability around the 2007 crisis period for the subsample of public banks. It also presents results on mechanisms that magnify/mitigate this relationship. The dependent variables used are overall market risk and idiosyncratic risk of a bank during the crisis period. Overall market risk is computed as the standard deviation of market return. Idiosyncratic risk is computed as the standard deviation of the residuals obtained from estimating the following equation for each bank: $r_{i,t} = \alpha_i + \beta_{1,i}\, r_{m,t} + \beta_{2,i}\,(Baa - Aaa)_t + \beta_{3,i}\,(3 - month\, T - bill)_t + \epsilon_{i,t}$ where $r_{m,t}$ is the weekly S&P500 market return, $(Baa - Aaa)_t$ is the default risk factor (difference between yields on a *Baa* and *Aaa* rated corporate bonds), and $(3 - month\, T - bill)_t$ is the interest risk factor (change in the yield of a 3-month treasury bill). The main independent variable, *Degree links*, is computed as the natural logarithm of the weighted degree of interconnections. *Dummy High Other Leverage/ Securitization/ Liquidity* is an indicator identifying banks with above median exposure to average leverage/securitization activity/liquid holdings of other banks in markets where the bank originates loans. 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)				Indiosyncratic Risk (crisis)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Degree Links)	0.013***	0.007	0.011*	0.033***	0.014***	0.008	0.011**	0.033***
	(0.005)	(0.006)	(0.006)	(0.007)	(0.004)	(0.006)	(0.005)	(0.007)
log(Links) * Dummy High Other Leverage		0.012				0.011		
		(0.009)				(0.008)		
Dummy High Other Leverage		-0.045				-0.040		
		(0.033)				(0.031)		
log(Links) * Dummy High Other Securitization			0.014*				0.013*	
			(0.009)				(0.008)	
Dummy High Other Securitization			-0.052				-0.048	
			(0.033)				(0.031)	
log(Links) * Dummy High Other Liquidity				-0.019**				-0.019**
				(0.009)				(0.008)
Dummy High Other Liquidity				0.058*				0.056*
				(0.034)				(0.032)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	273	273	273	273	273	273	273	273
R-squared	0.142	0.150	0.150	0.213	0.113	0.122	0.121	0.186