From Housing Bust to Credit Crunch: Evidence from Small Business Loans*

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Abstract

This paper provides evidence that the recent housing bust in the United States precipitated a "credit crunch" for small businesses. Using detailed records of individual bank's lending history, we develop a measure of their exposure to the housing bust. This measure is then used to estimate the impact of a drop in house prices on the supply of loans. Specifically, we compare the lending behavior of banks in the same metropolitan areas, and find that those that originated more of their mortgage loans in depressed housing markets elsewhere reduced local small business lending more substantially. We find the effect to be greater for banks with more than $10bn in assets. Overall, our estimates suggest that the fall in house prices accounted for one third of the decline in small business loans originated by major banks from 2007 to 2009.

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1 Introduction

Small businesses are particularly vulnerable to fluctuations in credit supply due to their reliance on financial institutions for external funds. Following

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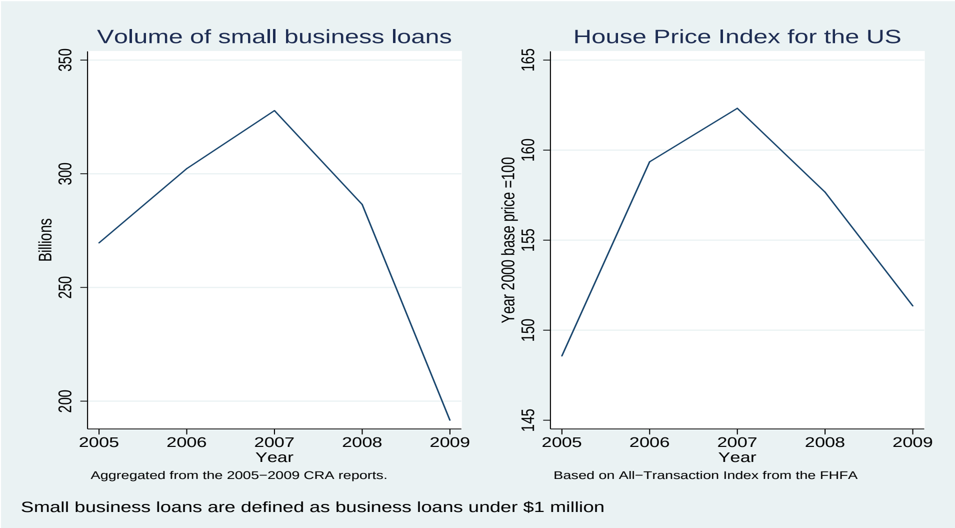
the downturn in 2007, the volume of newly-originated small business loans in the U.S. fell substantially. Among financial institutions that submitted data to the reporting program under the Community Reinvestment Act (CRA), the total volume of business loans less than \$1 million declined from \$328 billion in 2007 to \$192 billion in 2009, a drop of 41 percent. As CRA-reporting institutions in 2007 accounted for 86 percent of the U.S. banking industry's total domestic assets, and 64 percent of the outstanding small business loans (U.S. Small Business Administration, 2009), a reduction of this magnitude can only be described as a crash.

Figure 1: Newly-originated small business loans and house prices in the U.S.



The lending crash resulted from factors on both the demand and supply sides of the market. The economic recession that began in late 2007 has likely reduced the demand for loans, as well as lowered the credit worthiness of many firms. On the supply side, the availability of credit may also have been reduced. In the absence of any financial imperfections, banks would always grant loans to worthy applicants, regardless of the state of their own portfolio. The credit crunch hypothesis, however, suggests that banks do not have perfect access to credit markets. Rather, a deterioration in banks' financial health can lead to a reduction in the supply of credit, which may amplify an economic decline.

A housing downturn is among the most likely causes of a credit crunch, especially for bank-intermediated funds, as banks are exposed to the housing market through mortgage lending. A housing bust can force them to retreat from other types of lending, and thus spill housing losses over to the rest of the economy. Indeed, there is evidence that a typical housing bust in industrialized countries is associated with a greater decline in GDP than is a typical equity bust (Helbling and Terrones, 2003). Small businesses are particularly vulnerable, as they are more dependent on bank loans for external funds and more likely to rely on "relationship lending" with specific banks.[1]

The objective of this paper is to identify and assess the contribution of housing-related bank losses on the supply of small business credit between 2007 and 2009. Our approach separates supply from demand by comparing banks making small business loans in the same Metropolitan Statistical Areas (MSAs). Heterogeneity across lenders is correlated to bank-specific factors, where our focus is on bank's exposure to housing busts across the nation. Specifically, it uses individual bank's history of mortgage lending to construct a proxy for their exposure to falling housing markets across the nation. We find that banks that originated more of their mortgage loans in areas that subsequently experienced greater declines in house prices reduced their small business lending more substantially. This is in line with the credit crunch hypothesis, as our findings suggest that a bank's willingness or ability to lend is not independent of its capital position.

Our approach bypasses two identification problems that hinder empirical investigations into credit crunches. First, we separate supply and demand-side factors using within-MSA-year variations, assuming that banks operating in the same area in a given year face similar changes in demand for loans and borrower quality. This is similar to the approach taken by Bernanke and Lown (1991), who studied the possible role of a credit crunch during the 1990 recession using data on banks in the state of New Jersey. Secondly, it avoids using a bank's own capital condition to explain its loan dynamics. The condition, as pointed out in Peek and Rosengren (1995), could reflect the economic health of the bank's relationship borrowers, which in turn has impacts on demand for loans. Our approach is akin to using housing exposure to instrument for potentially endogenous loan losses. Prior the analysis, we confirm that our proxy for housing exposure is significantly correlated with indicators of banks' financial health.

The empirical strategy allows us to calculate the aggregate impact of the housing-led credit crunch. The proxy for housing exposure is constructed

[1] Relevant discussion can be found in Gertler and Hubbard (1988), Gertler and Gilchrist (1994),Brewer et al. (1996) and Berger and Udell (1998).

based on changes in house prices in areas where the bank is exposed. At the aggregate level, the entire banking sector is exposed to the entire country. Nationwide changes in house prices can thus be used to calculate the crunch's impact on aggregate loan origination. Our estimates suggest that 37 percent of the decline in small business loans from 2007 to 2009 can be attributed to the bust in house prices.

Our findings show substantial heterogeneity across banks of different sizes. Specifically, the largest banks (those with $10 billion in assets or more) cut back lending more substantially in response to the decline in house prices. This finding may help explain a curious survey observation that small business customers of the 18 largest banks in the US were less successful in obtaining the desired credit in 2009 compared to customers of other banks; the gap in success rate was as large as 20 percentage points (Dennis, 2010). The lending retreat by large banks is quantitatively important as they are important suppliers of small business loans, in terms of coverage as well as loan volume.[2] It is not clear what caused the big banks to respond differently. We can only speculate that they might have greater off balance sheet exposures to the housing market, different business models or faced greater scrutiny and regulatory uncertainty after the crisis began. A better understanding of the underlying causes will help identify factors affecting the supply of small business credit going forward.

The paper proceeds as follows: Section 2 reviews relevant literature. Section 3 describes the empirical strategy. Section 4 describes the data. Section 5 presents the findings and robustness tests. Section 6 concludes.

2 Literature Review

This paper contributes to the literature on credit crunches, the influence of the housing market on financial stability, and the vulnerability of small businesses to financial frictions. We discuss each in turn.

Credit crunch: Holmstrom and Tirole (1997) formalized a theoretical link between bank capital and a credit crunch. In their model, financial intermediaries, whose function is to channel funds from savers to firms with investment projects and to monitor borrowers against moral hazard, are

[2]Our calculation based on the 2005-2009 call reports shows that lending institutions with more than $10 billion assets hold about half of the outstanding small business loans with original amounts less than $1 million. A 2009 survey of small business by the National Federation of Independent Businesses, reported in (Dennis, 2010), found that 46 percent of small businesses used one of the 18 biggest banks in the US as their primary bank.

themselves constrained by incentive problems. Because monitoring involves nonverifiable costs, banks face a moral hazard problem and are required to inject some of their own capital into the firms that they are monitoring. Their model suggests that even if a bank has the capacity to monitor an unlimited number of firms, the actual amount of monitoring, and thus its lending, is constrained by the bank's own capital. A credit crunch, resulting from a reduction in the supply of intermediary capital (or an increase in capital requirement), will reduce aggregate investment and increase interest rate spreads.

Holmstrom and Tirole (1997) treats intermediary capital as exogenous. Potentially, a bank can respond to capital losses by raising new equity. But this may be complicated by a lemons problem in the equity market (Myers and Majluf (1984)), especially in times of uncertainty.[3] If a bank faces a binding capital constraint and high cost of raising new capital, it has little choice but to respond to capital losses by reducing lending. Thus a widespread deterioration in banks' capital conditions can lead to a contraction in credit availability and a reduction in economic activity.

There were a number of empirical investigations into this phenomena during and after the 1990-91 recession, a period in which many economists suspected that the US, especially in New England, suffered from a lack of credit availability (see, for example, Syron, 1991). The major hurdle in these studies was separating a reduction in the supply of credit (credit crunch) from a decrease in the demand for loans and the worsening of creditworthiness of borrowers, both of which would reduce loan volume. Bernanke and Lown (1991) dealt with the problem in part by comparing the lending behavior of banks within a single state (New Jersey), in order to control for the general economic conditions. They concluded that the credit crunch was not a major cause of the recession, and demand side factors were responsible for much of the slow down.

Peek and Rosengren (1995) also used bank-level data from a single area to help control for demand-side factors (in this case New England). In their analysis, the authors pointed out another endogeneity problem in that loan demand across banks might be correlated with the shocks to bank capital. Specifically, they stated that "if a bank's borrowers are tied to the bank through historical relationships, bad outcomes for those firms would cause loan losses (reducing the bank's capital) and also weaken loan demand"

[3]In Myers and Majluf (1984), firms have the option to raise new equity to finance a profitable project. But because the management of firms know the true quality of their existing asset better than investors do, a good firm's shares are under-priced in a pooling equilibrium. Under some conditions, only low-quality firms will issue new equity.

(Peek and Rosengren, 1995, p. 633). Their empirical approach was based on a model of profit-maximizing banks, which predicts that a bank would reduce deposit taking in response to capital losses if it faces a binding capital/asset constraint, but would increase deposit taking if the constraint is not binding. Their estimations used deposit growth as the dependent variable instead of the lending growth. Their findings were consistent with the hypothesis of a "capital crunch" in New England.

The subsequent analysis bypasses both of the above mentioned identification problems. First, it separates supply-side forces from demand by using within-MSA variation, comparing banks that are operating within the same MSAs in a given year. Similar to Bernanke and Lown (1991), the paper assumes that banks operating in the same area face similar aggregate demand for loans and credit quality of borrowers (local effects are controlled for using MSA-year dummies). Heterogeneity across lenders is accredited to bank-specific factors, where our focus is on the exposure to housing busts. Unlike Bernanke and Lown (1991), this paper is a nationwide study, which is befitting the scale of the financial turmoil in the last decade.

To address the second identification problem, the endogeneity associated with bank's capital condition, we use bank's nationwide housing exposure to predict local loan growth. One can think of this as using housing exposure as an instrument for the bank's capital condition. The housing measure is nationwide because it is calculated based on a bank's exposure to all MSAs where they have mortgage operations. To ensure that the measure does not capture local influences, which may be correlated with local demand for loans, the construction of the exposure measure excludes all local information. The availability of non-local information is a benefit of using a dataset with a national coverage.

Finally, we note several studies on bank lending during the recent credit crisis. Ivashina and Scharfstein (2010) compared the lending behavior of banks that had different exposures to Lehman Brothers, and found that those that co-syndicated more of their credit lines with Lehman reduced syndicated lending more substantially after the Lehman failure. Our paper focuses on small businesses loans instead of large corporate loans, however, the identification strategies are similar. Ivashina and Scharfstein (2010) used Lehman exposure to proxy for the disruption in credit supply, our paper uses exposure to housing busts for a similar purpose. Carlson et al. (2011) matched U.S. banks based on geographic area, size and other business characteristics to study the relation between capital ratios and loan growth since 2001, and found the relation to be insignificant until the recent crisis when it became positive and "fairly strong." Focusing on liability structure, Goetz and Gozzi (2010) found that small U.S. commercial banks that were more reliant on wholesale liabilities reduced their lending relatively more between 2007 and 2009. Our paper adds to the body of evidence by focusing on small business loans and by linking the credit crunch to housing busts. Furthermore, we employ an empirical strategy that avoids the potential endogeneity concern arising from using banks' own financial conditions as noted in Peek and Rosengren (1995). There are also studies on the cross-border transmission of the the recent banking crisis, examples including Puri et al. (2010) and Popov and Udell (2010), who used Germany data and Central/Easter European data, respectively. Iyer et al. (2010) studied the impact of the freeze of the European interbank market in August 2007 on the supply of bank credit to businesses in Portugal.

Housing busts and the supply of credit: A credit crunch may result from a negative shock to bank's financial conditions, which can arise for a variety of reasons, including a residential or a commercial real-estate bust. Syron (1991) suggested that a credit crunch had resulted from a real-estate bubble in New England in the early 1990s. He argued that New England banks aggressively sought lending opportunities in the real-estate sector in the mid-1980s, and suffered extensive loan losses from the subsequent drop in real-estate prices. The loss in equity capital forced banks into downsizing, reducing credit availability, particularly for bank-dependent small firms.

Helbling and Terrones (2003) surveyed asset price booms and busts in industrialized countries, and found that output losses associated with housing price busts were twice as large as those associated with equity price busts (8 versus 4 percent). They interpret these results as reflecting the greater wealth effect of house prices on consumption,[4] and the greater exposure of the banking system to real-estate lending. Consistent with the bank-exposure hypothesis, they found that housing price busts, relative to equity busts, had greater negative effects on banks' capacity and willingness to lend. They also found that, across industrialized countries, bank-based financial systems tended to suffer larger output losses in housing busts compared to market-based financial systems (see also the discussion in Trichet, 2005).

Historical correlation can be difficult to interpret however. Mishkin (2007), suggests that housing busts are often the by-product of banking crises. One example is the Nordic banking crisis, which he suggests was

[4]Case et al. (2005) finds from aggregate data that the effect of housing wealth on household consumption is larger than that of stock wealth.

primarily caused by commercial lending collateralized by commercial real-estate, even though house prices dropped shortly beforehand.

The vulnerability of small business to financial frictions: Our focus on small business loans is in line with a sizable literature that uses small business data to study financial frictions. Examples include Petersen and Rajan (1994), Gertler and Gilchrist (1994), Bernanke et al. (1996) and Berger et al. (2001). There are a variety of theories that suggest that small firms are more likely to suffer from imperfections in the financial market due to a lack of collateral capital and reputation. Holmstrom and Tirole (1997) predict that a loss of intermediary capital affects first firms that are poorly capitalized, because of the scale economies of monitoring. The financial accelerator model in Bernanke et al. (1999) also suggests that small businesses, due to their greater agency costs of borrowing, are likely to experience greater decline in access to credit following a negative macroeconomic shock. The "life-cycle" theory of credit access of Diamond (1991), suggests that new firms will try to build up their reputation by subjecting themselves to bank monitoring before issuing debt directly in the public market. Finally, we note a number of studies on relationship lending that focus on small businesses (Petersen and Rajan, 1994; Berger and Udell, 1995; Degryse and Van Cayseele, 2000; Berger et al., 2001).

3 The empirical strategy

Let $L_{i,j,t}$ denote the volume of small business loans originated by bank i in metropolitan statistical area (MSA) j at time t. We will use $\Delta L_{i,j,t}$ to indicate $L_{i,j,t} - L_{i,j,t-1}$. A change in $L_{i,j,t}$ may reflect changes in credit demand, supply, or both.

The reduction in the volume of small business loan in the US from 2007 to 2009 occurs in conjunction with a major recession. Ceteris paribus, a negative economic shock to MSA j will reduce the demand for loans and/or increase credit risks in the area. Presumably, this results in a reduction in $L_{i,j,t}$, even when banks are willing to lend to qualified borrowers. Thus, to detect and quantify a credit crunch, our estimates must separate the supply from demand-side effects. This is achieved by including MSA dummies in regressions attempting to explain $L_{i,j,t}$. This way, we compare the lending behavior of banks that are making the same type of loans (small business loans) in the same metropolitan areas. Within-MSA-inter-bank differences are then correlated to individual bank's exposure to the housing market *across the nation* with local influence excluded. The hypothesis is that banks that are more exposed to housing busts are more likely to reduce lending than those that are less exposed.

We now characterize the expression that will be the focus of our estimation.

$$\frac{\Delta L_{i,j,t}}{\bar{L}_{i,j}} = \sum_j \alpha_{j,t} D_j + \beta X_{i,t,excl(j)} + \gamma Z_{i,j,t} + u_{i,j,t} \tag{1}$$

The dependent variable is the scale-adjusted changes in small business lending from year $t-1$ to t by bank i in MSA j. The denominator $\bar{L}_{i,j}$ is the average yearly lending volume of the bank-MSA pair.[5]

On the right hand side, the first term includes the MSA-year dummy variables that absorb changes in local demand and credit worthiness from $t-1$ to t in MSA j. The variable $X_{i,t,excl(j)}$ in the second term is the measure of bank i's exposure to the housing market from year $t-1$ to t, excluding local influences from MSA j. The exact expression of $X_{i,t,excl(j)}$ is given in equation (2) below. Intuitively, it is a proxy for year-to-year changes in the market value of houses that a bank accepted *in the past* as pledged collateral for its outstanding mortgage loans. The set of collateral are evaluated using market prices in year t, and then again at market prices at $t-1$. The proportional change over the period is the X at t. Thus, the methodology is parallel to the calculation of CPI inflation using a basket of goods, except that the basket in our calculation consists of pledged collateral. A gain (loss) in the value of pledged collateral indicates the bank's exposure to a rising (falling) market. To construct the measure exactly, we would need to know the market value of individual houses, which is information that we do not have. We do however, know the amount of the loan borrowed against the houses, their general locations, and the house price index in those locations. We thus approximate the collateral value as the principal amount of mortgage loans multiplied by the factor of house price appreciation in the MSA, adjusted for repayment history. Finally, we exclude the local MSA in the calculation as a precaution to ensure that the measure of housing loss is exogenous to local markets.[6]

[5] Scale adjustment, as opposed to differences in log, is used to a) avoid losing data points when a bank-MSA pair has zero small business lending in a given year but positive origination in other years; b) avoid, to some extent, creating greater volatility from using a small numerator in calculating proportional changes.

[6] A local housing bust will likely have a greater impact on banks that are proportionately more concentrated in the local area, relative to their nationwide size (smaller banks for example). If local influences were not excluded, the inter-bank differences in $X_{i,t}$ may in part reflect size differences as banks of different sizes may respond differently to a local

Formally, $X_{i,t,excl(j)}$ is characterized by the following expression.

$$X_{i,t,excl(j)} = \frac{\sum_{s=1}^{N} \sum_{j' \neq j}^{M} [(1-\delta)^s L^g_{i,j',t-s} \frac{P_{i,j',t}}{P_{i,j',t-s}}]}{\sum_{s=1}^{N} \sum_{j' \neq j}^{M} [(1-\delta)^s L^g_{i,j',t-s} \frac{P_{i,j',t-1}}{P_{i,j',t-s}}]} - 1 \qquad (2)$$

On the right hand side, the integer N is the length of the window of lending history in years. The integer M is the total number of MSAs. The variable $L^g_{i,j,t-s}$ for $s = 1, 2, ..., N$ describes bank i's history of mortgage lending in MSA j. The parameter δ is the annual rate of repayment, assumed to be constant. Thus the term $(1-\delta)^s L^g_{i,j,t-s}$ indicates the outstanding balance of loans from the year $t - s$. The ratio $P_{i,j,t}/P_{i,j,t-s}$ is the factor of price appreciation from year $t - s$ to the current year t, so that $(1-\delta)^s L^g_{i,j,t-s} \times P_{i,j,t}/P_{i,j,t-s}$ is the current-market value of housing assets that have been pledged to the bank. The denominator on the right hand side of equation (2) is similarly constructed, except that the house price from year $t-1$ is used. Taken as a whole, the right hand side of equation (2) indicates the price inflation of a basket of collateral assets; a lower value indicates a greater exposure to MSAs with falling house prices.

Our primary focus is on the estimation of β in equation (1), which measures the impact of the bank's mortgage market exposure on its volume of small business loans. If β is estimated to be zero, there is no spillover effect from the mortgage market (and no credit crunch). If β is positive, the estimate can be used to evaluate the contribution of the housing bust to the decline in small business loans.

We note that the changes in loan volume are quite volatile at the bank-MSA level. Besides the standardization strategy mentioned above, we will also eliminates trivial bank-MSA pairs that are small in size or infrequent in loan origination. As well, we control for the size of banks and the size of bank-MSA operations in our regressions, and adjust standard errors for heteroskedasticity. Finally, we allow errors to cluster at the level of individual banks, given that most banks in our sample operate in multiple areas.

4 Data

Estimation of equation (1) requires information on small business loans, mortgage lending and changes in house prices. This section explains the nature and sources of the data and describes the construction of the housing exposure variable X.

downturn, which may in turn contaminate the estimates.

Data on small business loans

The lending records of small business loans come from the annual reports submitted by depository institutions to federal regulators under the Community Reinvestment Act (CRA). The reports are used to help evaluate reporting institutions on their "record of meeting the credit needs of its entire community, including low- and moderate-income neighborhoods" (Community Reinvestment Act October 12, 1977). Reporting is mandatory for large institutions. The asset size threshold was $1 billion in 2005, and has increased over time due to inflation adjustment. CRA used to require smaller institutions to report as well. A 2005 easing of the requirement gives such banks the option to stop reporting, however many continue to do so.[7] These CRA-reporting institutions accounted for 86 percent of total domestic assets and 64 percent of outstanding small business loans in the U.S. banking industry in 2007, according U.S. Small Business Administration (2009), based on comparison with the Call Reports. Among other information, the public CRA data contain county-level aggregate volume of small business loans originated by individual banks in a calendar year. The availability of loan location is crucial to our identification strategy.

The small business loans in the CRA data are defined as business loans with less than $1 million (at origination), which will include small credit to big businesses. However, since small businesses are more likely to borrow small amounts, it has been common in the literature to use loan size as a proxy for borrower size.[8]

Our empirical strategy calls for comparing bank lending in the same metropolitan areas. We thus aggregate the total amount of loans to the level of bank-MSA combinations. There are more than 40 thousand such combinations that have records of non-zero lending between 2005 and 2009, but many had negligible volume or frequency. We eliminate from our analysis the bank-MSA pairs that reported less than $100,000 per year on average

[7]Before 2005, CRA required all banks with assets over $250 million and any member banks of a bank holding company with assets over $1 billion to report to the program. The 2005 regulatory revision allow such banks to stop reporting and be examined under new procedures for their CRA compliance. But the new regulation also gives smaller banks the option to be examined under the old procedures, provided that they continue to collect data and report to the CRA program (see http://www.fdic.gov/news/news/financial/2006/fil06033.html). In 2009, 39% of the 877 reporting institutions (without consolidating the ownership) had less than $1 billion assets as of the December of 2008.

[8]Examples include Peek and Rosengren (1998); Strahan and Weston (1998); Frame and Woosley (2004); Berger et al. (2005), as well as the annual study on lending to small and micro businesses by the U.S. Small Business Administration.

in the five-year window, and those that reported non-zero origination in only one year during the period. These trivial pairs account for less than 2% of the total loan volume.

We are interested in the changes in loan volumes during the 2007-2009 period. Each bank-MSA pair, indexed by (i, j), has at most two data points in our sample (the change from 2007 to 2008 and the change from 2008 to 2009). The lending information from 2005 to 2009 are used to construct $\bar{L}_{i,j}$, the average yearly loan volume used to standardize the scale across bank-MSA pairs.

Our final sample, after further losses of observations when merged with external information, contains 381 MSAs, 773 banks in 2008, and 771 banks in 2009.[9] In terms of pairings, there are 12,274 bank-MSA pairs in 2008, and 11,863 pairs in 2009. For base-line analysis, we do not consolidate bank ownership to Bank Holding Companies (BHCs), because not all member banks of a BHC face mandatory reporting since the 2005 easing of reporting requirement; changes in CRA loans aggregated to BHCs therefore may be caused by member banks flowing in or dropping out of the reporting program. In a robustness test, we aggregate bank-level loans to BHCs using only member banks that have reported in consecutive years. The results from the BHC-level analysis are very similar to those based on bank-level data.

The sample has good coverage in terms of loan volume. Table 1 shows that the sample accounts for almost 80 percent of the small business loans reported in the CRA data in 2008 and 2009.

Table 1: Volume of small business loans (in billions) originated by bank-MSA pairs in our regression samples compared to the national aggregates reported in the CRA program

Year	CRA aggregate	Full sample	Subsamples: Top 10% (big banks)
2008	286.5	218.0	157.0
2009	191.6	150.7	102.8

[9] The sample also has thrifts that are responsible for about 10 percent of total small business loans. For ease of exposition, we refer to banks/thrifts simply as banks. The two-year sample together contains 824 banks that are uniquely identified by respondent ID and regulatory agency code. A small number of banks changed their charter types during the period. We regard them as different institutions at different points in time.

In addition to the full sample, we also consider a subsample consisting of the top 10 percent largest banks, ranked by their consolidated asset sizes as of December 2008.[10] There are 82 such banks. They are responsible for the majority of the bank-MSA pairs because they operate in more MSAs than other banks. They also originated a large majority of small business loans in our sample (see Table 1). Table 2 describes the distribution of bank sizes in the sample. The smallest bank in the top 10 percent has an asset size of $10.15 billion.

Table 2: The size of bank assets ($ billion)

Group	Mean	SD	Min	Max	N
Top 10% by asset size	115.15	288.52	10.15	1746.24	82
The rest	1.86	1.85	0.07	9.90	742

Data on housing exposure

We now describe the information needed to construct the housing exposure variable X. The records of mortgage lending come from the annual reports submitted by mortgage lenders as required by the Home Mortgage Disclosure Act (HMDA). Among other information, the HMDA's Loan Application Register (LAR) database identifies loan amount, mortgage lenders and the census tract of property location. In this paper, we aggregate the loan information to the MSA level for individual lenders. HMDA is believed to cover a large majority of mortgage loans in the U.S. In 2007, almost 9,000 lenders filed an HMDA report. Avery, Brevoort, and Canner (2007) found that HMDA-covered lenders together account for approximately 80 percent of all home lending nationwide. HMDA reports both home-purchase loans and refinancing loans; both will be used to construct X. The HMDA also reports loans purchased by banks in the secondary market, which are excluded here to avoid double counting.

The house price index is from the Federal Housing Finance Agency. The All-Transactions Index is used because it is the only one that is available for all MSAs. The numbers are reported quarterly and we use simple averages to convert it into a yearly index.

In order to construct X, it is necessary to choose the length of the history window, which we denoted above by N. The window needs to cover the

[10] Or as of December 2007 if the bank did not submit the 2009 CRA report.

period when mortgage delinquency or foreclosure are the most likely, taking into account that distant vintages are more likely to have been repaid. Gerardi et al. (2008) analyzed homeownership experiences in Massachusetts over the 1989 to 2007 period, tracking the same borrowers for the same residential property. Their data show substantial variation in the trajectory of default hazard rates between different cohorts of loans, reflecting their findings that homeownership outcomes are highly sensitive to initial loan-to-value ratios and the movement of house prices after origination. In terms of the price trajectory after origination, the closest parallel to the sample used in our paper may be the Massachusetts 1989 cohort, originated before the large price decline in the New England area in the early 1990s (which many argue led to a credit crunch; see the literature review). This cohort's default hazard rate peaked between 3 and 5 years after the origination (figure 13 of Gerardi et al. (2008)). With this in mind, we experiment with window lengths ranging from 3 years to 6 years. All provided qualitatively consistent and quantitatively comparable estimates. For the sake of brevity, only results from the 4 and the 6-year window are presented in the paper. The annual repayment rates δ, is set at 10 percent per year so that three quarter of all loans are repaid after 15 years. This is somewhat arbitrary, but we found that varying δ has little impact on the estimates.

It is important to note that not all loans are kept on balance sheets by their originators. A substantial portion are sold in a secondary market, where buyers include Government-Sponsored Enterprises (GSEs), private-label securitizers of Mortgage Backed Securities, institutions affiliated with originating banks, and other banks or financial institutions. The HMDA data is limited in this aspect, as it records individual loan destinations only in the calendar year of origination. As it is unclear exactly how one should treat loans which have been sold, we do so in two ways. As a default we only use loans that were kept by the originating bank on its balance sheet in the initial year, because loans sold to certain buyers (GSEs in particular) were likely final, so that their subsequent performance would have little impact on the original lenders. This approach is less than ideal however, because banks can still sell the loan in later years. Unfortunately, the HMDA does not contain such information, so it is not possible to trace loans over the entire period. One could also argue that solely focusing on loans kept on the balance sheet is insufficient. For example, some of the so-called "sales" were in fact regulatory arbitrage, when the originating bank sold the loan to affiliated institutions or off-balance sheet vehicles to influence their capital/asset ratio. In some situations, these banks may have provided implicit guarantees for the performance of these loans. The Financial Crisis Inquiry Commission has found that "[d]epository institutions and their holding companies provided extraordinary support to nonbank subsidiaries and off-balance sheet vehicles...Citigroup and Wachovia purchased assets from their Structured Investment Vehicles, which they had no contractual obligation to do." (page 13, FCIC (2010)). Thus, we estimate the model with an alternative formulation of X, which is constructed using values for L^g that are expanded to include loans sold to affiliate institutions. All together, we have four alternative formulations of $X_{i,t,excl(j)}$ that differ both in N and the definition of L^g.

The housing exposure variable is constructed as weighted averages of changes in local house price indices. For an individual bank, the exposure variable is the weighted average of the price changes across MSAs in which it provides mortgage loans. As we expect, the exposure variable for the entire banking sector is similar to the nationwide changes in house prices. This can be seen in Table 3, which compares the changes in the US house price index to the sector-wide exposure variable (namely the weighted average in the full sample). The four alternative constructions of X have similar averages, and the table shows the values generated using the X that has a four-year window and includes only loans kept on the balance sheet (hereafter it will be our default unless specified otherwise). From 2007 to 2009, the exposure variable indicates a 10.4 percent fall in house prices, while the US house price index fell by 7 percent. Table 4 describes the housing exposure variable broken down by bank size.

Table 3: Housing exposure and the US house price index

Year	Housing exposure (*N=4; loans kept by lender*)	Changes in US house prices from previous year
2008	-.051	-.029
2009	-.053	-.041

Source: Authors' calculation and the FHFA.

Our basic hypothesis is that housing busts can lead to bank losses, and may force banks to reduce lending even if demand conditions remain the same. We test the first part of the hypothesis by relating X to indicators of bank losses. The first indicator is loan loss provisions, the injection of funds to the allowance for loan and lease losses. The data on loan loss provisions are obtained from the mid-year Call Reports, and are expressed as a ratio to

Table 4: Housing exposure by bank size

	Mean	Sd	Min	Max	N
The 2008 sample					
Top 10% by asset size	-0.051	0.048	-0.167	0.035	79
Others	-0.032	0.058	-0.322	0.051	694
The 2009 sample					
Top 10% by asset size	-0.055	0.032	-0.145	0.012	75
Others	-0.043	0.043	-0.237	0.024	696

the size of assets. In a sample of about 690 banks with matching information, the correlation between the housing exposure and the loss provisions is negative and highly significant. Figure 2 shows the scatter plots.

Figure 2: Loan loss provisions and the proxy for housing exposure

Our second indicator is an extreme form of bank losses: bank failures. We use the exposure variable to predict the probability that a bank failed in the coming year. We manually matched the list of failed banks maintained by the FDIC to the list of CRA banks. We then use the X in 2008 (which measures changes in the value of underlying mortgage assets from 2007 to 2008) to predict failures in 2009, and the X in 2009 to predict failures in 2010. In both years, a probit model overwhelmingly rejects the null hypothesis that X has no influence on the probability of bank failures in the coming year. We can also see the relation from some simple statistics.

Of the 26 banks that failed in 2009, who have submitted the CRA reports a year ago and for whom we have the necessary information, the average of their housing exposure is -9.5 percent. The rest of the banks had an average of -3.6 percent. For the 18 banks who failed in 2010, the average housing exposure is -7.5 percent; for banks who survived, it is -4.2 percent.

5 Findings

This section presents the estimates of β characterized in equation (1). Besides the MSA dummy variables, the baseline model contains only the most basic information, including the asset size of banks, the operation size of bank-MSA pairs (the average annual volume of small business loans from 2005 to 2009), and dummy variables for federal supervisory agencies (FRS, FDIC and OTS, with OCC-supervised banks as the omitted group).

Table 5 presents the estimates from the full sample. Each of the four columns represents a different construction of $X_{i,t,excl(j)}$ described in section 4. The upper and the middle panels show separate-year estimations for 2008 and 2009, respectively. The lower panel shows the estimation for the pooled sample. The separate-year estimations include MSA effects. The pooled-year estimation allows MSA*year effects to account for changes to local conditions over time.

All regressions provide positive estimates of β, which we interpret as evidence of housing-led credit crunch. Comparing estimates between years, we find that the estimated effects of housing exposure are smaller from the 2008 sample than from the 2009 sample, but they are more precisely estimated. The estimates from the 2008 sample are all statistically significant at 5 percent or better. In contrast, those from the 2009 sample have large standard errors, some only with borderline significance. Since the between-year differences are all within two standard errors, we pool together the two years' observations for summary estimates, allowing MSA*year effects in the process. As expected, the resulting estimates for the housing variables are greater than those from the 2008 sample, and smaller than those from the 2009 sample. The four alternative ways of constructing the exposure variable yield similar estimates that range from 2.05 to 2.36, with standard errors about 0.7.

Tables 6 and 7 give our estimates for the subsamples described above. Table 6 includes only the largest 10 percent of banks by asset size. Table 7 uses the other 90 percent banks. The two samples have comparable numbers of observations because large banks operate in a larger number of metropolitan areas. To save space, these tables present only the estimated effects for the housing exposure variable, even though the other variables in the baseline model are always included in the regressions.

Comparing across subsamples, we find that the top 10 percent of banks produce substantially higher estimates than the rest. Judging by the pooled two-year estimations in the lower panel, we find that the sample of the largest banks produces estimates almost four times the size of those from the sample of other banks (4.2 versus 1.2 with the default measure with $N = 4$ and loans kept by lenders). The greater sensitivity exhibited by these top banks is rather paradoxical, as they typically have smaller shares of assets secured by real estate on the balance sheets.[11] But it is consistent with observations from a 2009 survey of small businesses sponsored by the National Federation of Independent Business (NFIB). The survey, reported in Dennis (2010), found that small businesses whose principal bank was one of the 18 largest commercial banks in the nation (accounting for 46 percent of respondents) had substantially greater difficulty in accessing credit. Specifically, the survey finds that "just under 30 percent of small business customers of the largest institutions who attempted to borrow [in 2009]...obtained all the credit they wanted. Meanwhile, half (50%) of small business customers of the remaining commercial banks...obtained all the credit they wanted" (p. 8). The gap in the success rate does not disappear even after controlling for credit scores. The NFIB report, which deemed the gap "highly curious", speculates that it may reflect the effect of different approaches toward small businesses lending, with smaller banks employing more relationship lending while big banks' using "more mechanical credit scoring methods" (p. 22). Our analysis suggests that the extra credit crunch facing customers of the largest banks is likely a result of, at least in part, the extra sensitivity of those banks to housing busts. It also suggests that the difference in lending approaches is unlikely to be a sufficient explanation, as the reduction in credit supply is not uniform among big banks and is significantly correlated with housing exposures.

What could then explain the extra sensitivity exhibited by the largest banks? We are not able to offer a conclusive explanation in this paper. We can only speculate that big banks might have greater off-balance sheet housing exposure, or that big banks might have regarded small business lending as being more dispensable in time of crisis. Another possibility is

[11] Regressing loans secured by real estate, i.e., RCFD1410 in the Call Reports, as a share of total consolidated assets on the logarithm of asset sizes produces a coefficient of -.037 with a standard error of 0.0044.

that the largest banks faced greater scrutiny from regulators during the crisis because of their systemic status, which could have made them more sensitive to capital losses.

Robustness tests

In this subsection we describe a series of robustness tests performed on the model. First, we estimate equation (1) using data from the 2005-2007 period. Recall that the purpose of estimating equation (1) is to detect a credit crunch if one exists. In the 2005-2007 period, a credit crunch was unlikely to have existed. Will equation (1) still detect a positive relation between housing exposure and loan growth as it does with the 2007-2009 data? If so, it could call into question the validity of the empirical strategy.[12] Table 8 presents the comparison. We use the same set of banks that overlap the two periods. The comparison shows that the housing exposure had no relation with changes in small business lending between 2005 and 2007; the estimated effects are negative and insignificant for either the 2006 or the 2007 estimations. In contrast, positive and statistically significant effects are found in the 2008 and the 2009 estimations. The contrast points to important differences between the 2005-2007 period and the 2007-2009 period.

Next, we add to the baseline model variables describing the risk features of banks, specifically banks' deposit to liability ratio and the security to assets ratio, both from the June Call Report of the previous year. The purpose is to control for differences in risk management between banks.[13] The inclusion of the two risk variables, one on the asset side and the other liability side, causes little change in our estimates (see Table A.1 in the appendix). In the pooled 2008 and 2009 estimation for all banks, the estimated coefficient on the default measure of housing exposure ($N = 4$; with loans kept by lenders) was 2.31 without the security and deposit ratios (in the second column of the lower panel, Table 5); it becomes 2.34 when those ratios are included (in the first column, Table A.1); the estimates' standard errors are about 0.7 in both cases. Subsample estimations continue to indicate greater sensitivity among the largest banks.

[12] Our sincere thanks go to Kristopher Gerardi and Teodora Paligorova for the suggestion.

[13] A bank that is less averse to risk may have more of their mortgages from areas prone to housing busts, and more of their business loans lent to risky borrowers. In a housing downturn, falling prices creates negative exposure for the bank, while the ensuing recession reduces the credit demand from risky borrowers. This creates a positive correlation between housing exposure and small business lending without involving a credit crunch; controlling for MSA effects may not be sufficient.

The next two tests remove subsets of banks from the regression sample. First, we remove the top 10 biggest banks ranked by the number of MSAs in which they operate. These banks are responsible for a large number of observations in the sample; removing them from the regression may give smaller institutions a better chance to influence the estimates.[14] Table A.2 reports the findings, showing that the removal has little impact on the estimate of interest. Before the removal, the default measure of housing exposure ($N = 4$; with loans kept by lenders) has a coefficient of 2.31 in the full-sample-pooled-year estimation with a standard error of 0.72. The same coefficient rises to 2.45 with a standard error of 0.70 after the removal. Furthermore, the difference between the top 10 percent banks and other banks persists.

The second test removes banks that are known to have acquired failed banks in the 2008-2009 period, plus Bank of America and Wells Fargo that have gone through well-known merger cases.[15] A total of 54 banks are removed, but the results are little changed (in Table A.3).

In the next robustness check, we repeat the analysis at the level of Bank Holding Companies (BHCs) to pick up possible spillover effects within BHCs. Due to the changes in the reporting requirement in 2005, member banks of a BHC no longer face mandatary reporting requirement unless they cross certain asset size thresholds, while those below the threshold have the option to stay in the program or cease reporting. As a result, the entrance and exist of member banks will create fluctuations for BHC-level aggregate loan volumes in the CRA. To get consistent time series from one year to the next, we use focus on banks that submitted consecutive CRA reports, adding up their loan volumes if they belong to the same BHC. When calculating housing exposure, we use as many member banks as we can find from the call report to capture within-BHC spillovers.[16] With BHC-level aggregations, it is no longer meaningful to separate mortgage loans kept by lending banks and those sold to affiliates; so we use the sum of the two as a proxy for loans kept within BHCs. Tables A.4 report the estimates, which are little changed compared to those from the bank-level data. Take the full-sample-pooled-year estimates as examples. The estimated coefficient

[14]The 10 banks are Wells Fargo Bank, N.A., Chase Bank USA, N.A., JPMorgan Chase Bank, N.A., Bank Of America, N.A., US Bank North Dakota, American Express Bank, FSB, Wachovia Bank, N.A., US Bank, N.A., Regions Bank, and State Farm Bank.

[15]The list of failed banks and acquiring banks is from the list maintained by the FDIC.

[16]The membership in a BHC is identified with Regulatory High Holders in the call reports. Banks that are not in a BHC, or single-bank BHC, continue to be treated as single entities.

for our measure of housing exposure is 2.19 (with a standard error of 0.69) from the BHC-level data and 2.36 (with an identical standard error) from the bank-level data in the first column of Table 5. The difference between top banks and smaller banks persists.

The last test uses an alternative strategy to deal with heteroskedasticity. Instead of using a White correction, we use the Feasible Weighted Least Squares (FWLS) method, weighting observations with the inverse of variance predicted based on bank sizes, bank-MSA sizes and the MSA*year dummies. Table A.5 shows the estimates, which are qualitatively consistent with those from the White corrections. The estimates tend to be about a quarter smaller in sizes, but are all statistically significant at the 5 percent confidence level. The difference between top banks and smaller banks remains.

Quantifying the impact of the credit crunch

We now quantify the impact of the housing-led credit crunch. We note that the point estimates for housing exposure's impact on credit extension are sensitive to bank size. In particular, the estimated effects are substantially greater in the sample of the largest banks than in the sample of smaller ones. We will proceed with the full-sample estimates from the pooled 2008-and-2009 regressions, because they use the maximum amount of information. There is no clear choice between the four alternative characterizations of housing exposure variables and in any case they provide quantitatively similar estimates, so we take the average across all four.

Using the estimate, we approximate the impact of the recent housing bust on the decline in small business loans across the entire United States. The coefficient β measures the impact of changes in house prices on the lending of small business loans. The percentage nationwide impact will be the product of the estimated β and a measure of nationwide changes in house prices. The nationwide price index from the Federal Housing Finance Agency indicates that US house prices fell by 7 percent from 2007 to 2009 in terms of annual averages. Using the full-sample average estimate of $\hat{\beta} = 2.23$, the price drop is thus estimated to reduce small business lending by $7 * 2.23 \approx 16$ percent of the average loan volume. In order to filter out changes from banks moving in or dropping out the CRA reporting program, we consider only those that submitted CRA reports throughout the 2007-2009 period. The average yearly aggregate lending volume by these banks during the period is \$247 billion, 16 percent of which is \$39.5 billion.[17]

[17] These banks as whole originated \$290.6 billion small business loans in 2007, \$266.9 billion in 2008 and \$184.6 billion in 2009.

Thus, 37 percent of the \$106 billion decline from 2007 to 2009 observed among these banks can be accredited to the fall in house prices.

6 Conclusion

This paper presents evidence that the recent housing bust in the United States has led to a credit crunch for small businesses. In our attempt to quantify this supply-side phenomenon, we utilize within-MSA variations to control for the influence of demand-side factors. Specifically, we compare the lending behavior of banks in the same metropolitan areas, and find that those that originated more of their mortgage loans in depressed housing markets elsewhere reduced local small business lending more substantially. As our proxy of housing exposure is constructed based on changes in house prices, its estimated coefficient can be used with data on home prices nationwide to calculate the contribution of the recent housing bust to the fall in small business loans across the nation. Our estimates indicate that the housing-led credit crunch is responsible for a third of the decline in small business loan origination from 2007 to 2009.

We also find that the largest banks (those with assets of \$10bn or more) are more sensitive to the housing bust, reacting with substantially greater reductions in lending. This may explain why small business customers of the largest banks had greater difficulty in accessing credit during the crisis than customers of other banks, as reported in a 2009 survey by the National Federation of Independent Business. It remains to be explained why the largest banks behaved differently. It may be the result of their off-balance sheet housing exposures, their approach to small business lending, or the greater scrutiny and regulatory uncertainty that they faced. As big banks are an important source of small business credit, a better understanding of their hesitance to lend is important, as the economy proceeds into the recovery stage with credit demand picking up and credit supply becoming increasingly important.

Table 5: Full sample estimations

DV	Year-to-year changes in lending of small business loans in proportion to average loan volume between 2005 and 2009			
	N=4		N=6	
$X_{i,t,excl(j)}$ uses	loans kept by lender or sold to affiliates	loans kept by lender	loans kept by lender or sold to affiliates	loans kept by lender
2008 Estimation				
$X_{i,t,excl(j)}$	1.99 (0.77)***	1.77 (0.78)**	2.02 (0.76)***	1.78 (0.77)**
Log of bank-MSA size	-.01 (0.01)	-.009 (0.01)	-.009 (0.01)	-.009 (0.01)
Log of bank's asset size	-.03 (0.02)	-.03 (0.02)	-.03 (0.02)	-.03 (0.02)
FRS banks	-.14 (0.09)	-.13 (0.09)	-.13 (0.09)	-.13 (0.09)
FDIC banks	-.16 (0.11)	-.16 (0.11)	-.15 (0.11)	-.15 (0.11)
OTS thrifts	-.21 (0.15)	-.21 (0.15)	-.21 (0.15)	-.21 (0.15)
Obs.	12274	12274	12274	12274
R^2	0.04	0.04	0.04	0.04
2009 Estimation				
$X_{i,t,excl(j)}$	3.08 (1.47)**	3.34 (1.51)**	2.57 (1.37)*	2.57 (1.32)*
Log of bank-MSA size	0.0005 (0.01)	0.001 (0.01)	0.001 (0.01)	0.001 (0.01)
Log of bank's asset size	0.002 (0.02)	0.002 (0.02)	0.0000316 (0.02)	-.001 (0.02)
FRS banks	-.08 (0.13)	-.08 (0.13)	-.08 (0.13)	-.08 (0.14)
FDIC banks	-.09 (0.09)	-.09 (0.09)	-.08 (0.1)	-.08 (0.1)
OTS thrifts	-.61 (0.17)***	-.61 (0.17)***	-.61 (0.17)***	-.61 (0.17)***
Obs.	11863	11863	11863	11863
R^2	0.06	0.06	0.06	0.06
Pooled 2008 and 2009 Estimation				
$X_{i,t,excl(j)}$	2.36 (0.69)***	2.31 (0.72)***	2.20 (0.68)***	2.05 (0.67)***
Log of bank-MSA size	-.005 (0.008)	-.004 (0.008)	-.004 (0.008)	-.004 (0.008)
Log of bank's asset size	-.02	-.02	-.02	-.02

Continued on next page...

	(0.01)	(0.01)	(0.01)	(0.01)
FRS banks	-.11	-.11	-.11	-.10
	(0.08)	(0.08)	(0.08)	(0.08)
FDIC banks	-.12	-.12	-.12	-.12
	(0.08)	(0.08)	(0.08)	(0.08)
OTS thrifts	-.40	-.41	-.40	-.41
	(0.1)***	(0.09)***	(0.1)***	(0.1)***
Obs.	24137	24137	24137	24137
R^2	0.06	0.06	0.06	0.06

Notes: (1) *, **, and *** indicate statistical significance at 10%, 5% and 1% levels. (2) The numbers in the parentheses are heteroskedasticity-robust standard errors that also allow clustering by banks. (3) Yearly regressions include MSA effects; pooled estimations include MSA*year effects. (4) The dependent variable is expressed as a fraction relative to the average loan volume between 2005 and 2009. (4) The column headings explain the construction of the explanatory $X_{i,t,excl(j)}$. The variable is also expressed as a fraction. (5) The indicator of OCC-supervised banks is the omitted dummy variable.

Table 6: Subsample estimations - Top banks

DV	Year-to-year changes in lending of small business loans in proportion to average loan volume between 2005 and 2009			
	N=4		N=6	
$X_{i,t,excl(j)}$ uses	loans kept by lender or sold to affiliates	loans kept by lender	loans kept by lender or sold to affiliates	loans kept by lender
2008 Estimation:				
$X_{i,t,excl(j)}$	4.21 (1.47)***	3.79 (1.56)**	4.13 (1.42)***	3.69 (1.52)**
Obs.	6854	6854	6854	6854
R^2	0.07	0.07	0.07	0.07
2009 Estimation:				
$X_{i,t,excl(j)}$	4.63 (3.01)	5.10 (2.95)*	3.74 (2.91)	3.70 (2.85)
Obs.	6469	6469	6469	6469
R^2	0.08	0.09	0.08	0.08
Pooled 2008 and 2009 Estimation				
$X_{i,t,excl(j)}$	4.35 (1.41)***	4.24 (1.47)***	4.07 (1.38)***	3.75 (1.40)***
Obs.	13323	13323	13323	13323
R^2	0.08	0.08	0.08	0.08

Notes: (1) *, **, and *** indicate statistical significance at 10%, 5% and 1% levels. (2) The numbers in the parentheses are heteroskedasticity-robust standard errors that also allow clustering by banks. (3) To save space, the table presents only the estimated effects for the variable of housing exposure. Other variables in the baseline model are always included in the regressions; but their estimated coefficients are not shown.

Table 7: Subsample estimations - Other banks

DV	Year-to-year changes in lending of small business loans in proportion to average loan volume between 2005 and 2009			
	N=4		N=6	
$X_{i,t,excl(j)}$ uses	loans kept by lender or sold to affiliates	loans kept by lender	loans kept by lender or sold to affiliates	loans kept by lender
2008 Estimation				
$X_{i,t,excl(j)}$	0.41 (0.6)	0.38 (0.59)	0.39 (0.58)	0.36 (0.57)
Obs.	5420	5420	5420	5420
R^2	0.07	0.07	0.07	0.07
2009 Estimation				
$X_{i,t,excl(j)}$	2.64 (1.43)*	2.64 (1.44)*	2.19 (1.17)*	2.21 (1.18)*
Obs.	5394	5394	5394	5394
R^2	0.1	0.1	0.1	0.1
Pooled 2008 and 2009 Estimation				
$X_{i,t,excl(j)}$	1.22 (0.64)*	1.21 (0.64)*	1.03 (0.6)*	1.02 (0.6)*
Obs.	10814	10814	10814	10814
R^2	0.09	0.09	0.09	0.09

Notes: (1) *, **, and *** indicate statistical significance at 10%, 5% and 1% levels. (2) The numbers in the parentheses are heteroskedasticity-robust standard errors that also allow clustering by banks. (3) To save space, the table presents only the estimated effects for the variable of housing exposure. Other variables in the baseline model are always included in the regressions; but their estimated coefficients are not shown.

Table 8: Robustness tests: compare estimates from the 2005-07 data to those from the 2007-09 data

$X_{i,t,excl(j)}$ uses	N=4; loans kept by lenders			
	Period 2005-07		**Period 2007-09**	
	2005 to 2006	2006 to 2007	2007 to 2008	2008 to 2009
$X_{i,t,excl(j)}$	-.484	-.146	1.798	3.658
	(0.817)	(1.028)	(0.811)**	(1.576)**
Log of bank-MSA size	0.006	-.007	-.009	0.001
	(0.015)	(0.012)	(0.013)	(0.015)
Log of asset size	0.016	0.022	-.034	0.002
	(0.021)	(0.017)	(0.023)	(0.021)
FRS supervised banks	-.069	0.048	-.134	-.089
	(0.077)	(0.09)	(0.089)	(0.136)
FDIC supervised banks	-.056	0.157	-.150	-.095
	(0.062)	(0.084)*	(0.116)	(0.099)
OTS supervised banks	0.08	0.426	-.211	-.675
	(0.129)	(0.197)**	(0.151)	(0.178)***
Obs.	11185	11894	11894	11251
R^2	0.034	0.039	0.038	0.067

Notes: (1) The dependent variables are always changes in the lending of small business loans, in proportion to the average loan volume from 2005-2009. (2) *, **, and *** indicate statistical significance at 10%, 5% and 1% levels. (3) The numbers in the parentheses are heteroskedasticity-robust standard errors that also allow clustering by banks.

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Table A.1: Robustness tests: adding banks' risk features into the model

$X_{i,t,excl(j)}$ uses	$N = 4$; loans kept by lender		
	Full sample	Top banks	Other banks
Pooled 2008 and 2009 Estimation			
$X_{i,t,excl(j)}$	2.335	3.981	0.791
	(0.66)***	(1.271)***	(0.42)*
Log of bank-MSA size	-.0009	0.002	0.0003
	(0.007)	(0.01)	(0.007)
Log of bank's asset size	-.022	-.020	-.019
	(0.012)*	(0.029)	(0.017)
FRS banks	-.028	-.017	-.068
	(0.071)	(0.109)	(0.044)
FDIC banks	-.055	-.133	-.030
	(0.057)	(0.103)	(0.036)
OTS thrifts	-.064		0.165
	(0.135)		(0.124)
Securities to asset ratio- Lag	0.725	1.847	-.058
	(0.299)**	(0.646)***	(0.16)
Deposit to liability ratio- Lag	-.630	0.092	-.625
	(0.221)***	(0.486)	(0.09)***
Obs.	21120	11511	9609
R^2	0.054	0.094	0.096

Notes: (1) *, **, and *** indicate statistical significance at 10%, 5% and 1% levels. (2) The numbers in the parentheses are heteroskedasticity-robust standard errors that also allow clustering by banks.

Table A.2: Robustness tests: removing 10 banks operating in the largest number of MSAs

$X_{i,t,excl(j)}$ uses	$N = 4$; loans kept by lender		
	Full sample	Top banks	Other banks
Pooled 2008 and 2009			
$X_{i,t,excl(j)}$	2.45	5.18	1.64
	(0.7)***	(1.76)***	(0.57)***
Log of bank-MSA size	0.01	0.007	0.01
	(0.006)*	(0.01)	(0.007)**
Log of bank's asset size	-.004	-.01	-.06
	(0.02)	(0.05)	(0.03)**
FRS banks	-.07	-.07	-.06
	(0.07)	(0.12)	(0.04)
FDIC banks	-.08	-.17	-.04
	(0.05)*	(0.1)	(0.04)
OTS thrifts	-.37	-.29	-.36
	(0.1)***	(0.13)**	(0.14)**
MSA-year effects			
Obs.	18143	7965	10178
R^2	0.06	0.11	0.09

Notes: (1) *, **, and *** indicate statistical significance at 10%, 5% and 1% levels. (2) The numbers in the parentheses are heteroskedasticity-robust standard errors that also allow clustering by banks. (3) The 10 banks are: Wells Fargo Bank, N.A., Chase Bank USA, N.A., JPMorgan Chase Bank, N.A., Bank Of America, N.A., Us Bank North Dakota, American Express Bank, FSB, Wachovia Bank, N.A., US Bank, N.A., Regions Bank, and State Farm Bank. The removal of these banks reduce the sample size by 5358, or 268 MSA per year per bank.

Table A.3: Robustness tests: removing banks involved in acquisitions in 2008-2009

$X_{i,t,excl(j)}$ uses	$N = 4$; loans kept by lender		
	Full sample	Top banks	Other banks
Pooled 2008 and 2009			
$X_{i,t,excl(j)}$	2.42	4.76	1.28
	(0.84)***	(1.73)***	(0.72)*
Log of bank-MSA size	-.005	-.02	0.008
	(0.01)	(0.02)	(0.009)
Log of bank's asset size	-.02	0.03	-.04
	(0.02)	(0.04)	(0.04)
FRS banks	-.07	0.05	-.18
	(0.1)	(0.16)	(0.11)*
FDIC banks	-.14	-.11	-.18
	(0.08)*	(0.13)	(0.09)*
OTS thrifts	-.40	-.32	-.49
	(0.1)***	(0.12)***	(0.18)***
MSA-year effects			
Obs.	19421	9431	9990
R^2	0.07	0.12	0.1

Notes: (1) *, **, and *** indicate statistical significance at 10%, 5% and 1% levels. (2) The numbers in the parentheses are heteroskedasticity-robust standard errors that also allow clustering by banks. (3) Fifty four (54) banks are removed from the sample; 52 of them are banks that acquired failed banks listed on the FDIC list; the other two are Bank of America and Wells Fargo for their acquisition of Merrill Lynch and Wachovia, respectively.

Table A.4: Robustness tests: consolidating ownership to BHC for member banks in the same BHC

$X_{i,t,excl(j)}$ uses	$N = 4$; loans kept by lenders or sold to affiliates (proxying for loans kept within BHCs)		
	Full sample	Top banks	Other banks
	(1)	(2)	(3)
2008 Estimation			
$X_{i,t,excl(j)}$	1.93	4.14	0.5
	(0.97)**	(2.10)**	(0.68)
Obs.	9186	5427	3759
R^2	0.04	0.08	0.1
2009 Estimation			
$X_{i,t,excl(j)}$	2.76	4.07	2.34
	(0.93)***	(2.18)*	(0.85)***
Obs.	8613	4914	3699
R^2	0.05	0.08	0.11
Pooled 2008 and 2009 Estimation			
$X_{i,t,excl(j)}$	2.19	4.03	1.12
	(0.69)***	(1.57)**	(0.48)**
Obs.	17799	10341	7458
R^2	0.05	0.08	0.11

Notes: (1) *, **, and *** indicate statistical significance at 10%, 5% and 1% levels. (2) The numbers in the parentheses are heteroskedasticity-robust standard errors that also allow clustering by banks. (3) Other variables in the regressions include the log of bank-MSA size, the log of bank's asset size, a dummy variables indicating the observation is a BHC or not, as well as dummy variables indicating the identity of regulatory agencies for banks that do not belong to a BHC.

Table A.5: Robustness tests: using Feasible Weighted Least Squares

$X_{i,t,excl(j)}$ uses	$N = 4$; loans kept by lender		
	Full sample	Top banks	Other banks
	(1)	(2)	(3)
$X_{i,t,excl(j)}$	1.73	3.39	0.78
	(0.7)**	(1.40)**	(0.38)**
Log of bank-MSA size	-.007	-.01	0.004
	(0.008)	(0.01)	(0.01)
Log of bank's asset size	-.01	0.005	-.02
	(0.01)	(0.03)	(0.03)
FRS banks	-.05	-.03	-.10
	(0.07)	(0.1)	(0.07)
FDIC banks	-.04	-.04	-.08
	(0.06)	(0.11)	(0.06)
OTS thrifts	-.37	-.44	-.30
	(0.07)***	(0.1)***	(0.16)*
MSA effects			
Obs.	24137	13323	10814
R^2	0.08	0.1	0.09

Notes: (1) *, **, and *** indicate statistical significance at 10%, 5% and 1% levels. (2) The numbers in the parentheses are standard errors cluster-adjusted by banks. (3) Details about the Feasible Weighted Least Squares method: we regress the log of squared OLS residuals on the logarithm of bank size, the bank-MSA size and the MSA*year dummies. We then use the exponential of the fitted value from the regressions as the predicted variance (the logarithm and exponential transformation is to avoid negative fitted values). We then use the inverse of the predicted variance as weights.