The Impact of Credit Shocks: Micro versus Small Firms*

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Abstract

Using novel data from the leading online accounting software in the United States with millions of financial transactions for small businesses, I measure firms' responses to shocks in credit supply during the Great Recession. Bank failures are associated with declines in credit for small firms but not micro firms. In contrast, movements in house prices are associated with credit changes for micro firms but not small firms. This suggests differences in how firms overcome asymmetric information, with micro firms depending more on housing collateral and small firms on lending relationships, consistent with associated costs to lenders.

Small businesses face asymmetric information in lending markets (Stiglitz & Weiss, 1981)[1]. Two widely-documented ways in which firms overcome this are (1) to set up lending relationships with banks where information is shared, and (2) to circumvent the problem by using collateral, which is often the personal assets of the business owner[2]. If the cost of acquiring information for the lender varies across firm size, there may be heterogeneity within small businesses in the channel with which the firm overcomes asymmetric information.

For very small loan volumes, banks may not find it profitable to incur the fixed costs of investing in a lending relationship but may still be willing to accept pledges of collateral as

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[1]Given the high skewness in the size distribution of firms in the US, the exact definition of "small businesses" doesn't change the number of small businesses based on cutoffs ranging from 50 to 500.

[2]Petersen & Rajan (1994); Uzzi & Lancaster (2003); Drexler & Schoar (2014) have studied the importance of lending relationships for small businesses, while Hurst & Lusardi (2004); Evans & Leighton (1990) have emphasized the role of the business owner's personal wealth in business performance.

basis for lending. If smaller firms have smaller loan requirements and do not access credit through lending relationships but through collateral, banking shocks may be less important for them given the frictionless movement to another lender to re-establish previous levels of credit, but movements in real estate prices may matter. For firms who borrow based on lending relationships, they may be frictions associated with banking shocks that lead to declines in credit.

Research on the role of credit supply for small businesses has gained importance in the context of the Great Recession, with a focus on the role of housing collateral and declining bank credit. Small businesses are especially sensitive to financial shocks given their credit constraints. In the Great Recession, small business credit growth declined more than that of larger firms, as shown in Figure 1. Empirical research in this area has been limited by data constraints in three ways. First, there is no readily-available data source for financials of small businesses. Second, measures of credit shocks are not available at the firm level for small businesses. Third, measures of *both* housing collateral *and* banking shocks are not at the firm-level for small businesses, restricting the comparison and combined study of the two shocks.

I use a novel dataset of financial transactions sourced from the leading online accounting software in the United States to study the response of small businesses to two shocks during the Great Recession which can disrupt the ability of small businesses to overcome asymmetric information in loan markets - bank failures and house price movements. Lending relationships can break down when banks fail, and large fluctuations in house prices can affect the ability of small business owners to access credit through housing collateral. Using my data, I am able to develop measures for *both* banking and housing collateral shocks at the *firm* level and thus build a comprehensive picture of the role of different types of credit for small business borrowing.

For the purpose of simplicity, I define two categories of firms based on the US Bureau of Labor Statistics nomenclature: "micro firms" are firms less than 10 employees, and "small firms" are small businesses with more than 10 employees. The dataset I use covers a wide range of micro and small firms for the years around the Great Recession, with the sample covering the period 2007 to 2013. Firms enter transactions and the software creates financial statements for book-keeping. The software allows firms to import their transactions from their business bank accounts directly, which generates a measure of a relationship between a bank and a firm. In addition, firm owners enter their personal contact information into the software, which I use to ascertain the home location of the business owner. I link the banks of firms in the dataset to the list of failed institutions published by the Federal Deposit Insurance Corporation, the agency responsible for the shutting down and restructuring of insolvent banks. I link the home address of the business owner to the median house price in the corresponding ZIP code, measured using the Zillow House Price Index. The ability to measure both banking and housing shocks at the firm level for a wide range of small businesses makes this dataset ideal for studying and comparing the impact of the two types of shocks on small businesses.

The first key result of the paper is that bank failures affect small firm credit but not micro firm credit. For small firms, levels of credit associated with bank failure are lower by 51% on average. The coefficients for micro firms are much smaller in magnitude and not statistically significant. This result is robust to a variety of specifications and in fact, the relationship between credit and bank failure is negative and monotonically increasing in magnitude with size within small businesses. The result is also robust to distinguishing micro and small firms based on size two years prior to bank failure, and controlling for firm age.

The channel of overcoming asymmetric information through lending relationships for small firms is supported by three findings. First, the impact of bank failures on firm credit is temporary; firm credit recovers after six quarters after bank failure. The recovery of firm credit is consistent with the absence of selection effects, and supports a story where firms facing bank failure encounter frictions with new lenders. Over time, these frictions may be overcome and previous levels of credit re-established. Second, the impact of bank failure is stronger for firms with fewer lending relationships at the time of failure. Firms linked to multiple lenders may be able to source credit with low additional costs from other lenders with whom they are already linked. Third, the length of the lending relationship with the failed institution matters for the difference in credit after the bank failure relative to before. With longer relationships, there are larger declines in credit following failure, supporting the channel of information sharing through lending relationships.

The second key result is that house price movements affect micro firm credit but not small firm credit. For micro firms, a 1% change in the house price index in the owner's ZIP code is positively correlated with a 0.2% change in long-term credit. The relationship between credit and house prices is monotonic with size. In this case, the coefficient of credit on the house price index is *decreasing* with firm size, in contrast to the trend for bank failures. This is consistent with micro firms using collateral to overcome asymmetric information, which would hold true if banks are unwilling to undergo costs of acquiring information for these firms.

There are relatively large real effects for firms through the credit supply channel. Both micro and small firms have declines in revenue associated with credit supply shocks and small firms show relationships between credit and employment as well. The differential impact of banking and housing shocks on micro and small firms also have implications for policy. Restructuring processes for troubled banks that take information embedded in lending relationships into account can prevent the loss of credit supply for small firms. Keeping rapid declines in house prices in check can maintain the stability of micro firm credit. Incorporating differential sensitivities of the two sets of firms into forecasting and policy design can inform questions on aggregate dynamics and business cycle effects through the channel of small business credit.

The paper proceeds as follows. In the next section, I will provide some background. In Section 2, I describe my dataset. Section 3 covers the empirical strategy. In Section 4, I will examine the response of firm credit to bank failures. In Section 5, I will study the role of house price movements on small business credit. In Section 6, I discuss additional results for both shocks, and Section 7 concludes.

1 Background

Small businesses face financial constraints due to asymmetric information in lending markets, which may be amplified during periods of economic contraction (Stiglitz & Weiss, 1981; Bernanke *et al.*, 1994). Financially constrained small businesses may be more sensitive to economic shocks, and given their importance in the economy can drive aggregate dynamics (Bernanke, 1983)[3].

Lending relationships that allow small, non-transparent firms to share information with lenders can play an important role in enabling access to credit (Petersen & Rajan, 1994). Firms may face tighter credit constraints when banks fail and information about the firm is lost, as documented for the Great Depression in Bernanke (1983). Bernanke attributes the decline in aggregate employment through the credit channel to the failure of more than 9000 banks during the Great Depression. Following this, the FDIC was set up in the 1930's to restructure troubled banks and to protect depositors and prevent contagion. The process of bank restructuring and changes in management involves transfer of loan officers. If firms depend on sharing information with banks through relationship lending, then bank failures may severe these relationship and disrupt the credit supply to firms. On the other hand, the role of lending relationships may matter less than has been documented in the Great Depression, due to advancements in IT in the banking sector that codifies soft information and if more information is transferrable across lenders Petersen (2004); Petersen & Rajan (2002).

[3]For the US, The Statistics of US Businesses (2014) reports that more than 99% of all firms have fewer than 500 employees, which account for almost 50% of total employment and more than 40% of total payroll. The share of small businesses is even higher in developing countries, for example see Hsieh & Klenow (2009).

The personal wealth of the business owner has also been shown to be important for firm credit. Business owners often use their personal collateral as a pledge for business loans (Hurst and Lusardi, 2004; Evans and Leighton, 1990), and access top-up credit as the value of the collateral rises. Large fluctuations in house prices during this period may affect the ability of small business owners to access credit.

Lower credit supply during the Great Recession has been studied in the context of declines in firm entry, increases in firm exit, and persistently high unemployment rates. Given data constraints, existing work is either limited to looking at firm-level measures for larger firms or aggregated measures for small businesses. There is still no concensus in the literature on the impact of banking and housing shocks for small businesses. Greenstone *et al.* (2014) use shocks to banking supply using changes in local composition of national banks to find that small businesses credit supply is impacted, but the employment effects are small. Chodorow-Reich (2014) finds large employment effects, but the firms studied are typically larger than the small businesses in the population. Adelino *et al.* (2015) study data from County Business Patterns published by the US Census Bureau covering a representative sample of US firms and find that the housing collateral channel matters for small businesses but not for larger ones. Chaney & Sraer (2012) find that real estate collateral matters for the credit of large, publicly-listed firms. This paper addresses the gap in the literature by using a new dataset that measures small business credit and shocks to it at the firm-level.

2 Data

Large-scale, high-frequency data on the financials of small firms in the US is limited. The AMADEUS and FAME datasets cover accounting data well for firms in the UK and Europe, but there are no such datasets for the US. Financial measures for large listed companies in the US are readily available from Compustat for large firms at relatively high (quarterly) frequency, but for smaller businesses, sources are limited. The Longitudinal Business Database and County Business Patterns published by the US Census Bureau measure entry, exit and employment for all US firms, but do not include financial information[4]. Information on financials is restricted to surveys, such as the Kauffman Firm Survey (KFS), the Survey of Small Business Finances (SSBF) or the Survey of Business Owners (SBO). These datasets have limited sample size and low frequency, with the KFS and the SSBF being conducted on a few thousand firms once every few years. Self-reported financial data raises concerns about

[4]Recent initiatives have included revenue measures at the firm-level in the Longitudinal Business Database - see Haltiwanger *et al.* (2016). However, detailed information on firm financials like credit or debt is not collected.

recall accuracy and misreporting (Kumler *et al.*, 2013), limiting the reliability of using these datasets.

I exploit a novel, private dataset from a leading online accounting software provider in the United States. Firms use the software for book-keeping, either in-house or in conjunction with an outside accountant. For obtaining reliable data for the study, I restrict the sample to all companies who have subscribed to the software, who have recorded business addresses, and can be matched to Dun and Bradstreet to measure additional background characteristics. I exclude accounting firms (NAICS 5412), which may be handling multiple companies under one account, non-profits and firms in non-classifiable industries (NAICS 99)[5]. The final sample consists of a panel of 141,678 firms for the period 2007-2013. Of these, 77,124 firms record relationships with banks.

Transactions are imported from the firm's business bank account or an employee of the firm enters them on a regular basis[6]. The data allows me to capture novel information on credit of small businesses, in particular the long-term liabilities and the links of businesses to banks. Time-varying financial variables are built from transactions using the timestamp of the transaction and the categorisation of the transaction into aggregate balance sheet and income statement items. Using the contact information for the owner, I extract the ZIP code for the owner's home address, to measure the relationship between movements in real estate prices in the owner's ZIP code and the firm's credit. The employment of the firm is a time-varying measure based on hiring and release dates[7]. Age and 6 digit NAICS industry are obtained from matching firms to Dun and Bradstreet.

Firms in the sample are representative of the US firm population in size and industry distribution. I compare data for 2010 for the population and the final sample. Population statistics of small businesses are sourced from the Statistics of U.S. Businesses, which summarizes Census data covering all employer firms[8]. Data Appendix Table A.6 shows the distribution of firms in the sample and the population across standard size bins. For both the sample and the population, there is a high concentration of firms at the lower end of the size distribution. For the population, approximately 80% of firms have less than 10 employees,

[5]Non-profit industries include NAICS codes 8139 (Administrators of Economic Development Programs) , 8134 (Business, Professional, Labor, Political & Similar Organisations), 9241 (Environment/Wildlife Safety & Conservation), 6241 (Family Social Services) , 8132 (Grant Making & Giving Services), 8139 (Homeowners Associations), 9251 (Housing & Urban Development Organisations) , 8133 (Human Rights Organisations), 6115 (Job Training Services), 7121 (Museums), 6200 (Non Profit Hospitals & Clinics) , 9221 (Public Safety Organisations), 8131 (Religious Organisations), 6100 (Schools & Libraries), 8133 (Social Advocacy Organisations), 8132 (Voluntary Health Organisations).

[6]Informal interviews with small businesses which use this software reveal that companies typically spend half a day during non-operating hours for bookkeeping and other administrative tasks.

[7]Owners sometimes include themselves and employees, and sometimes do not. For consistency, I exclude firms which record zero or one employees. This is not crucial for the results.

[8]I restrict the comparison to firms having less than 500 employees.

which is is about 70% in the sample. Another 12-14% have 10-20 employees, and there are only 1-2% firms with more than a 100 employees. Data Appendix Table A.8 compares the distribution of firms in the sample and the population across NAICS sectors. Both in the population and the sample, there is a high concentration of small businesses in Services at 71% for the population and at 77% for the sample. There is also a high share of firms in Retail, with 12% share in the population and 8% share in the sample. Construction covers 11% of firms in the population and 9% firms in the sample, and approximately 5% of small businesses are in Manufacturing. There are only about 1% small businesses in capital intensive sectors like mining and agriculture. The patterns across industries are also reflected in narrower 2 digit NAICS industries as shown in Data Appendix Table A.9.

Summary statistics for the sample as of March 2010 are shown in Table 1. Employment is defined based on the hiring and firing of employees based on entries in the software, and revenue is constructed by aggregating all transactions categorised under 'Income' by the business. Credit is measured as the sum of all transactions categorised as long-term liabilities where there is a transfer *from* a lender *to* the firm[9]. First, we see that the firms in the sample are small: from Panel A we see that the median firm size in the sample is 3 employees, and the mean is approximately 12[10]. The median firm in the sample earns about $300,000 in annual revenue. In comparison, Panel D shows the employment and revenue for Compustat firms for the financial year 2010. The firms in this sample are orders of magnitude larger. Note that the median credit across firm-years is zero, indicating that small businesses borrow infrequently. Appendix Figure A.1 shows the histogram of the number of months in a year that firms have positive credit for the set of firms which have at least one positive long-term liability transaction across all years in the sample. 48% of firms do not have long-term borrowing every year, and 19% borrow only once a year. Given the nature of borrowing of small businesses, long-term liabilities based on transactions are aggregated to the quarterly or annual levels for analysis.

[9]This is an aggregate measure of new long-term credit, and includes loans from banks and other credit lines, loans from friends and family members, SBA loans, and transfers from the owner's personal bank account to their business account. It excludes short-term liabilities such as credit card debt and accounts payable.

[10]I also show summary statistics for micro and small firms separately - micro firms are not only smaller than small firms by employment (by definition) but also by revenue. They also have lower levels of credit.

3 Empirical Strategy

To study the impact of bank failures on firm credit, I use bank closures and acquisitions assisted by the Federal Deposit Insurance Corporation (FDIC)[11]. 530 insolvent banks were dissolved with assistance during 2007-2013. Information on the failed banks including the date of dissolution is available from the list of failed institutions published by the FDIC. This captures the loss of lending relationships and any firm-specific information held by banks, focusing on the role of asymmetric information for credit. Firms may need to restart the process of sharing information, with either the acquiring institution or a new bank. Out of the 530 failed banks, 130 matched banks that firms in the software use for business accounts. Using this, I assign the date of bank failure from the FDIC to firms in the dataset. If firms still depend on sharing information with banks through relationship lending, then bank failures may severe these relationship and disrupt the credit supply to firms. This measures a time-varying banking shock at the firm-level.

House price movements change the price of the owner's personal collateral, which will matter in this setting for firms which cannot access bank credit through sharing information with lenders. The measure of house price shocks is constructed using the Zillow house price index, measured at the owner's home address. This is a monthly index constructed using all types of homes (single, condominium and cooperative), and estimates prices for homes that are not for sale as part of the calculation. Guerrieri *et al.* (2013) provide an in-depth description of the index including comparisons with other house price measures. The index is highly correlated with other house price indices, but has the advantage of being at the ZIP code level[12]. I aggregate the index to the quarterly or annual levels by averaging across months. I then match it to the ZIP code of the owner to give the measure of housing shocks.

3.1 Controlling for demand shocks

The main challenge in studying the role of credit supply shocks on small firm borrowing is controlling for local demand shocks. These are shocks which may both affect a firm's demand for credit and the supply of credit it faces. Omitting these can result in an upward bias of coefficient measuring the effect of credit supply shocks on firm credit. I use fixed effects in the regressions at the county-quarter level to control for local demand shocks. In the case of the banking shock, the identifying assumption relies on each county having many banks,

[11] Appendix Figure A.2 shows the share of firms in the population that failed every year across 2007-2013. Most bank failures occurred in 2009 and 2010. For the banks linked to firms in the sample, most bank failures occurred in 2008 and 2009.

[12] Correlation of the Zillow House Price Index is shown in Guerrieri *et al.* (2013). Also see Mian & Sufi (2012) where the correlation of the Zillow index with the Fiserv Case Shiller Weiss index is 0.91.

so that demand shocks in any given county are not exactly the same as credit supply shocks faced by firms. In the case of the housing shock, the validity of the assumption requires house prices to vary across ZIP codes *within* counties. I use quarter-county fixed effects to control for local demand shocks for bank failures as well as house price movements. The key question of the paper is the distinction in the effects of banking and housing shocks on firms of different sizes. Any demand shock that would go against the hypothesis would affect one size category of firms under one shock and the other category under the other shock, but not vice versa. Controlling for demand shocks, this paper examines whether credit supply shocks matter for firm credit.

4 Bank Failures and Firm Credit

4.1 Main Results

To examine the impact of bank failures on firm credit, I estimate the following equation for the set of small businesses in the dataset which have linked bank accounts -

$$Log(Credit_{it}) = \beta Fail_{it} + \theta_{tc} + f_i + e_{it} \tag{1}$$

where $Log(Credit_{it})$ is the log of the credit (measured as the sum of all long-term liability transaction *from* a lender *to* the firm) of firm i in time period t, $Fail_{it}$ is an indicator variable that takes value 1 if firm i has experienced a bank failure in the current or previous year for the annual analysis, and in the current or previous 6 quarters for the quarterly analysis[13]. The regression includes industry (or firm) fixed effects f_i. The coefficient of the regression of log credit on the dummy for bank failure may be upwardly biased if there are omitted local economic shocks which increase the probability of bank failure and simultaneously reduce the demand for credit from the firm's end. To control for local shocks, I include time-region fixed effects θ_{tc} (at the year-county level in the annual analysis and the quarter-county level in the quarterly analysis). The standard errors are clustered at the firm-level, to control for residual correlation across observations for the same firm across time. The percentage difference in the level of credit is -$(1 - e^{\beta}) \cdot 100$ where β is the coefficient of $Log(Credit_{it})$ on the dummy representing bank failure. With firm fixed effects and controls for shocks that drive credit demand, this coefficient can be interpreted as the *decline* in credit supply associated with bank failure.

[13] The measure of credit is an aggregate measure of new long-term credit, and includes loans from banks and other credit lines, loans from friends and family members, SBA loans, and transfers from the owner's personal bank account to their business account. It excludes short-term liabilities such as credit card debt and accounts payable.

Table 2 shows the results of estimating the relationship between credit measures and bank failure. Bank failures are associated with subsequent declines in firm credit and the results are driven by small firms. The effects are not large or significant for micro firms. Panel A uses quarterly data to estimate the relationship between $Log(Credit_{it})$ and bank failure. The dummy $Fail_{it}$ takes value 1 for the quarter of bank closure and the following six quarters. In column (1), the coefficient on bank failure is large and significant at -0.61, suggesting lower credit levels of 45% on average for one and a half years following bank failure. In column (2), controlling for firm fixed effects, the coefficient is smaller at -0.30, suggesting firm characteristics matter for the response of firm credit to bank failure, but still highly significant, and corresponding to a 26% decline in credit. The decline in credit associated with bank failure for micro firms is smaller in magnitude and not significant as seen in columns (3) and (4). For small firms, the coefficients are large in magnitude at -0.72 with industry fixed effects (corresponding to a credit decline of 51%) in column (5), and at -0.36 with firm fixed effects (corresponding to a decline in credit of 30%) in column (6).

The distinction between the responses of micro and small firms supports the hypothesis that within the small business universe, banks may be willing to lend to larger firms based on relationships. This can explain why bank failures are associated with lower firm credit - if firms were borrowing based on collateral or hard information, they could simply move to another lender in the event of bank failure, in which case they should not see disruptions in credit following the event of closure.

The distribution of credit to firms in different months of the year as shown in Appendix Figure A.1 shows that data on long term credit transactions is sparse. For this reason, I estimate the above equation at the annual level as well. In Panel B, I estimate equation 1 at the annual level. Column (1) shows the specification from equation 1 with industry fixed effects and year-county fixed effects as before. The coefficient is highly significant at -0.76, suggesting that bank failure is associated with 53% lower levels of bank credit. In column (2), the specification replaces industry fixed effects with firm fixed effects, to control for any firm-specific factors that drive firm credit as in Panel A. The coefficient is lower, suggesting that similar to results from the quarterly data, firm-level factors determine part of the relationship between firm credit and bank failure, as in the quarterly regressions of Panel A. It is still sizeable and significant at -0.56, corresponding to 43% lower credit associated with bank failure. The annual results are similar and in line with the quarterly results - bank closures are associated with almost tenfold larger declines in credit for small firms relative to micro firms.

Panel C looks at the outcome variable of $Log(Credit_{it}/Sales_{it})$. Scaling credit by sales accommodates the extent of external financing used by firms as a share of the business. The coefficients are in line with the results in Panel (A) and (B). In column (1) with industry fixed effects, the average difference in credit is large and significant at -0.57 (a difference of 43%), and significant at the 5% level. In column (2) with firm fixed effects, the coefficient is -0.62 (a decline of 46%), significant at the 1% level. For micro firms in columns (3) and (4), the coefficients are relatively smaller as well as insignificant. As before, the coefficient is higher for small firms as seen in columns (5) and (6). With industry fixed effects, the coefficient on $Log(Credit_{it}/Sales_{it})$ for small firms is -0.65, a difference of 48% in $Credit_{it}/Sales_{it}$, significant at the 1% level. With firm fixed effects in column (6), the coefficient of $Log(Credit_{it}/Sales_{it})$ on the dummy for bank failure for small firms is -0.66, which corresponds to a 48% decline in $Credit_{it}/Sales_{it}$ following bank failures for this set of firms.

In Panel D, the outcome measure is credit growth, defined as $0.5(credit_t + credit_{t-1})/(credit_t - credit_{t-1})$, based on Davis *et al.* (1998). The measure captures firm-time observations where the firm goes from taking zero credit to taking positive credit and vice versa, which adjusts for the high number of zero credit observations in the data. The measure is bounded below by -2, representing exit, and bounded above by 2 representing entry into positive credit. The results support that small firms respond to bank failures through credit growth, while micro firms do not. The coefficient from the regression of credit growth on bank failure for micro firms is not significant as in Panels (A)-(C). Bank failures are associated with a 0.37 percentage point decline in credit growth in the estimation of Equation 1 with industry fixed effects and a 0.5 percentage point decline in the estimation with firm fixed effects for small firms, supporting the results in previous panels.

The distinction between micro and small firms in the response of firm credit to bank failure is robust to changing the cutoff of firm size that defines micro vs. small firms. In fact, Figure 2 shows that the results described in Table 2 are monotonic in firm size. I plot the coefficient β for the estimation of equation 1 across standard employment bins from the US Census Bureau[14]. The graph suggests a monotonic trend in the relationship between firm credit on bank failure across firm size. This suggests that there is a shift from personal collateral based lending to lending based on relationships and information sharing as firm size increases.

[14] I use annual data, and given the sparseness of businesses in larger employment bins, the fixed effects used are the 2 digit NAICS industry and year-state level fixed effects.

4.2 Endogeneity Concerns

4.2.1 Robustness of Results

I check that the differences in results for micro versus small firms in Table 2 are robust to changing the cutoff of 10 employees that distinguishes micro firms from small firms. I have already shown in Figure 2 that the coefficient of log credit on bank failure is monotonic in firm size. In Panels A and B of Appendix Table A.1, I change the cutoff for micro vs. small firms to 5 and to 15 respectively. As expected from the monotonic trend in 2, the coefficient of log credit on closure for the cutoff of 15 is slightly larger than that for 10 at -0.85 relative to -0.76, which is in turn larger than the coefficients for the cutoff of 5 at -0.68. It still continues to hold that the coefficient of log credit on bank failure is significant for small firms but not micro firms.

Firm size may be endogenous to firm credit. To check this is not driving the results, I define firm size based on the number of employees *prior* to closure. In Panel C of Appendix Table A.1, I take the definition of micro and small firms two years prior to closure. The results are similar both in magnitude as well as significance to Table 2, with small firm credit being sensitive to bank failure but micro firm credit not significantly so.

Firms which are very small also tend to be very young (see for example Fort *et al.* (2013)). Appendix Figure A.3 shows the relationship between firm size and firm age in the sample. I plot the average firm size for employment size bins, and find that for bigger size categories, firms are on average older, consistent with findings in the literature based on the population of US firms (Haltiwanger *et al.*, 2013). This raises the concern that the difference in sensitivities of credit to bank failure for micro and small firms in Table 1 are driven by age differences for these firms rather than their size. To check whether this is the case, in Panel D of Appendix Table A.1 I control for firm age in the regressions for Panel D of Table 2. The table shows that credit is lower for older firms, but the coefficient of log credit on bank failure remains negative and significant, indicating a role for firm size.

4.2.2 Selection Effects

We may be concerned that banks which are more likely to fail may lend disproportionately to firms who have lower demand for credit or poorer performance. This selection of firms with lower demand by failing banks may be driving the results, instead of the disruption in credit *supply* due to the dissolution of lending relationships. I address this in three ways.

First, I check if firms which faced bank failures between 2007-2013 were different from firms which did not face bank failure, in 2006 on measures of credit and performance[15]. If

[15]The largest share of bank failures for firms in the dataset occurred in 2008 and 2009. Thus for most

the affected firms have lower credit and poorer performance when the bank was relatively healthy, selection may be driving the results. Panel (a) of Table 3 shows that there is no difference in credit, log credit and the log of the credit to sales ratio across the two groups. I also compare the difference in size measured by employment or log employment and find that there is no statistical difference in size between affected and unaffected firms.

The second check for selection effects is a placebo test checking differences in credit prior to failure. If banks which face failure tend to choose weaker firms, credit should be lower on average before the event of failure. I shift the dummy for failure back by one and a half years and rerun specification 1 to test this. For example, if a firm faced bank closure in 2008, the original dummy for failure in the annual data took value 1 in 2008 and 2009. The placebo dummy takes value 1 in 2006 and 2007 instead. If the coefficient of log credit on failure is significant prior to the failure of the bank, then the results in Table 2 may be driven by selection. As we can see in Table 3 Panel B, this is not the case: 2 years prior to bank failure we do not see significant differences in log credit.

Third, I run a placebo test for differences in credit 6 quarters after failure. If affected firms are not inherently weaker in credit demand or performance, we expect a temporary decline in firm credit following bank failure till the firm establishes itself with a new lender. If the firms linked to failing banks are inherently weaker, they are less likely to recover previous levels of credit with new lenders. I shift the dummy for bank failure *forward* by one and a half years and again run specification 1. From Panel (C) of Table 3, the difference in credit one and a half years after bank failure is very weakly significant after controlling for demand shocks. The coefficient changes sign and is not significant once firm fixed effects are included in the estimation. Firms which were linked to banks that failed were able to re-establish previous levels of credit, suggesting that they were not ex-ante weaker than firms linked to healthy banks.

To further demonstrate selection effects are not driving the results, I match firms affected by bank closure to firms which linked bank accounts in the software but did not face bank failures, and I compare outcomes for these sets of firms around the event of bank failure of the affected firm. The objective is to pair firms which are likely to face the same economic shocks, with pairing based on the probability of being selected into a match with a bank that may fail. More formally, I match "treated" firms (firms affected by bank failure) with "control" firms (firms not affected by bank failure) on the following variables which plausibly drive credit demand for the firm - log employment, log age, 4 digit NAICS industry, state and log credit, where the time varying variables log employment and log credit are measured

firms, these variables correspond to values around 2 or 3 years prior to the event of bank failure, when banks are plausibly not facing imminent failure or extreme distress.

1 year prior to the bank failure event. The firms are matched to similar firms using a propensity score, to overcome the potential selective matching of weaker firms to banks that are more likely to fail[16]. Firms which have similar observable characteristics should have similar demands for credit and based on their characteristics have access to similar lenders. Figure 3 show the results for an event study for the set of firms with more than 10 employees in 2008 and 2009 where event time 0 represents the quarter of failure for the treated firm[17]. The average difference in log credit for treated and control firms in matched pairs is shown for quarters before and after the event of bank failure in Figure 3. The evidence from the figure supports results from Table 5 - there is a decline in long-term credit for firms facing bank failures relative to similar firms which do not face failure. This difference is negative for approximately six quarters after closure. As in the placebo test, the pre-trend indicates that the credit was not significantly lower for the treated firms prior to the bank failure. This suggests that the lower credit following bank failure is not driven by selective sorting of weaker firms into banks that are more likely to fail.

4.2.3 Exits

Survivorship bias is another concern where we are measuring the effect of bank failure on log credit selectively for the survivors. More specifically, the concern is that bank failure might have such a strong impact on firms that they exit the market. In this case, especially if the impact on micro firms is so strong that they exit more relative to small firms, this could confound the result that bank failure impacts small firms but not micro firms. To test whether exit is predicted by bank failure, especially for micro firms, I estimate a linear probability model with a dummy for exit as the outcome variable and a dummy that identifies a three-year period following bank failure:

$$Exit_{it} = \beta Fail_{it} + \theta_{tc} + f_i + e_{it} \tag{2}$$

The results for the above regression are shown in Table A.2. From the table, exit is not predicted by bank failure, not for micro or for small firms. We can be less concerned that the results are driven by disproportionately large effects on micro firms that drive them to exit more than for the small firms[18].

[16] I take the calliper for the propensity score to be 0.01.

[17] 2008 and 2009 are the NBER defined recession years within the sample period and also have the highest number of bank closures affecting firms in the sample.

[18] More generally, the firms in the dataset have lower exit rates than those in the Census. This can be largely explained through firms in the sample being older and having large enough business volumes to use accounting software.

4.2.4 Reverse Causality

Another potential concern is reverse causality. Does the decline in firm credit demand lead banks to failure? Evidence from the literature suggests otherwise. Small business loans contribute a small share to the assets on a balance sheet of a bank. Jayaratne & Wolken (1999) measure the share of small business loans to be 3% of the balance sheet for large banks and 9% for large banks. Banks are more likely to be driven to failure due to exposure to the real estate market (Santos, 2011) or exposure to toxic assets (Erel *et al.*, 2014). They may also face failure due to contagion effects through being linked to specific institutions (Ivashina & Scharfstein, 2010; Chodorow-Reich, 2014).

4.3 Asymmetric Information

In this section, I document additional evidence that indicates the differences in responses to banking shocks are driven through the channel of asymmetric information.

4.3.1 Temporary Effect

In contrast to asymmetric information, another channel through which there is credit rationing in small business lending can be adverse selection (Stiglitz & Weiss, 1981). A bank will prefer its own existing borrowers rather than new firms, as a new firm may be adversely selected if other banks in the market are not already lending to it and may have refused it credit. If the channel of decline in firm credit is one of adverse selection rather than one of asymmetric information, we expect the decline in credit following bank failure to have lasting effects that may even worsen over time. However, we find that the impact of bank failure is most intense right after bank failure, and in fact it is no longer significant if measured 6 quarters following bank failure. This is shown in the previous section on selection effects, in figure 3 and in Panel C of Table 3. These results suggest that adverse selection is not driving the impact of banking failure on firm credit.

4.3.2 Number of Lenders

If firms are linked to multiple lenders, they may be able to source credit from them in the event of the dissolution of their primary lender. In this case, the relationship between bank failure and firm credit may be weaker. Small businesses typically have very few lending relationships. The distribution of the number of linked bank accounts for affected firms at the time of failure is shown in Appendix Figure A.4. 77% have one bank account linked, 19% have two banks linked, 4% have three banks and less than 1% have more than three banks linked.

To examine the role of the number of lending relationships, I split the sample by the number of linked banks of the affected firm at the time of failure. Panel A of Table 4 shows the regression of $Log(Credit_{it})$ on $Fail_{it}$ as in Column (1) of Panel D in Table 2, split across the number of linked banks for a firm in the software. This specification can be written as

$$Log(Credit_{it}) = \beta Fail_{i,t} + \theta_{qc} + f_i + e_{it} \tag{3}$$

where $Log(Credit_{it})$ is the log of credit measured as the sum of all long-term liabilities to the firm over a given quarter, $Fail_{it}$ is a dummy for bank failure that takes value one for the quarter of bank failure and six subsequent quarters. Fixed effects f_i are at the 2 digit NAICS level, and θ_{qc} measure local shocks at the quarter-county level as in the rest of the paper. Regressions are weighted by firm employment and standard errors are robust.

From Table 4 Panel A, we see that the impact of bank failure on firm credit varies across the number of banking relationships. Columns (1)-(3) show the results for all firms, and Columns (4)-(6) show the results for small firms. In Column (1) the coefficient of $Log(Credit_{it})$ on the dummy for bank failure is large and significant at the 1% level with value -0.64, which corresponds to a difference in average credit of 39%. Column (2) shows that for firms which had two linked bank accounts at the time of failure, the coefficient is -0.49 and still significant at the 1% level. This corresponds to lower credit of 33% on average, lower than the difference for firms with only one banking relationship. Column (3) estimates equation 3 for firms which have 3-5 banking relationships and faced failure. For this set of firms, the coefficient of log credit on bank failure is -0.20 which is lower than the coefficient for the subsample of firms with two relationships. We find similar trends for small firms, but with higher magnitudes for all columns, in line with the results from Table 2 where small firms are more sensitive to banking shocks. With one bank, the coefficient is large and significant at the 1% level with value -0.76 corresponding to lower credit of 53% on average. In contrast, if a small firm has 2 linked banks at the time of bank failure, the coefficient of Log Credit on failure is -0.56 and significant at the 1% level (corresponding to 43% lower average credit). With 3-5 banks, the coefficient of Log Credit on bank failure for small firms is -0.20, which translates to 18% lower average credit. These results support the hypothesis that the impact of bank failure on firm credit is through the channel of breakdown of lending relationships.

4.3.3 Length of Relationship

In this section, I explore how the length of the relationship with the bank that fails matters for the impact on credit of the firm linked to the bank. The typical firm that is impacted by bank failure is linked to the bank for an average of about 14 months. We may expect that for longer relationships of firms with banks, there are larger declines in credit following bank failure.

To estimate this, I estimate the following specification:

$$Log(Credit_{it}) = \beta Fail_{i,t} + \theta_{qc} + f_i + e_{it} \tag{4}$$

where $Log(Credit_{it})$ is the log of credit measured as the sum of all long-term liabilities to the firm over a given quarter as throughout the analysis, $Fail_{it}$ is a dummy for bank failure that takes value one for the quarter of bank failure and six subsequent quarters. Fixed effects f_i are at the firm level, and θ_{qc} measure local shocks at the quarter-county level. Regressions are weighted by firm employment and standard errors are robust. This specification, has firm fixed effects, allowing us to measure the decline in credit for a firm following bank failure. The results of this regression are shown in Panel B of Table 4.

From the table, we see that firms have larger declines in credit following a bank failure if they had a longer lending relationship with the bank that fails. Column (1) replicates the regression from Table 2 but with firm fixed effects for all firms. In Column (2), I rerun the regression looking at the firms which faced bank failure and had lending relationships with banks that failed that were longer than the median relationship length. This coefficient is higher in magnitude at -0.33 than that in Column (1) of -0.30, indicated that the difference in credit is larger following a bank failure if the firm had a long relationship with the bank. In Column (3), I similarly look at firms which had above mean length of lending relationships with failing banks, finding the results in line with the results on median relationship length but higher, with -0.36 decline in $Log(Credit_{it})$ associated with bank failure. These results are amplified when we focus on the set of firms sensitive to bank failure - small firms with more than 10 employees. For this set of firms again, having longer relationships with lenders breaking down leads to larger declines in credit, with -0.41 for above median length of the relationship and -0.39 for above mean length, relative to -0.36 for the overall sample. This is consistent with the impact of bank failure on firm credit being through the channel of relationship lending between firms and banks.

5 House prices and Firm Credit

Collateral can be especially important for micro firms if banks are unwilling to invest in lending relationships for smaller loan volumes that firms of this size may demand. To study the relationship between movements in house prices and firm credit for firms in the sample, I estimate the following equation -

$$Log(Credit_{it}) = \beta Log(HPI_{zt}) + \theta_{tc} + f_i + e_{it} \tag{5}$$

where $Log(Credit_{it})$ is the log of the credit (measured as before by the sum of all long-term liability transaction *to* the firm) of firm i in time period t, $Log(HPI_{zt})$ is the Zillow House Price Index matched to the ZIP code of the owner's home address[19]. The regression also has industry (or firm) fixed effects f_i. As in the case of bank failures, the coefficient of the regression of log credit on the dummy for bank failure can be biased upwards if local economic shocks are omitted. These are any local shocks which lead consumer wealth to increase with rising house prices, consequently increasing the demand for local goods and services (Mian & Sufi, 2012). In response to rising consumer demand, small businesses may demand higher credit, which will increase the coefficient on house prices in Equation 5. To control for such shocks, I include county-time fixed effects θ_{tc} which are at the quarterly or annual level depending on the specification. Standard errors are clustered at the zip-code level.

I estimate Equation 5 at the quarterly and annual level, similar to the specification for estimating the effects of bank failure. In addition, I also estimate it for two samples - the first is the sample with all firms who report owner addresses in the software. The second is the sample of firms who report lending relationships. Without the distinction between micro and small firms, we may expect that firms which are smaller in size would be more sensitive and have stronger responses to all credit shocks. We should expect micro firms to respond to bank failures if small firms do, and possibly *more* than they respond to house price movements, as bank failures are arguably a larger shocks to credit. One concern is that micro firms that report bank relationships in the data are less credit sensitive than micro firms in the larger samples, which would explain why bank failures impact the credit of small firms but not micro firms. To ascertain whether differences in samples are driving the results, I estimate the above equation for the subsample of firms that report lending relationships, used in the estimation of the impact of bank failure on firm credit.

5.1 Main Results

Table 5 shows the results from estimating Equation 5. I regress $Log(Credit_{it})$ on $Log(HPI_{zt})$ where HPI_{zt} is the Zillow House Price Index, which measures the median house price in a zipcode in a given time frame. Thus, the coefficient can be interpreted as the percentage change in credit with a 1% change in the median house price in the ZIP code.

[19]To match the firm data, the Zillow index has been aggregated to annual and quarterly levels by averaging across the original monthly frequency.

In Panel A, I use quarterly data for all firms in the sample to estimate the sensitivity of firm credit to house prices. Columns (1) and (2) show a weak positive relationship between firm credit and house prices. However, when we focus on the subset of micro firms in Columns (3) and (4) with industry and firm fixed effects respectively, we find the relationship between firm credit and the house price index to be highly significant at the 1% level. With controls for 2 digit NAICS, the coefficient for micro firms is 0.23 in column (3) , suggesting that a 1% change in the House Price Index corresponds to 0.22% difference in firm credit. In the case of firm fixed effects in column (4), a 1% increase in house prices is associated with a 0.33% change in credit supply to micro firms. Columns (5) and (6) show the relationship between house prices and firm credit for small firms, which is smaller in magnitude relative to the coefficients for micro firms and is not significant. The specifications control throughout for local demand shocks. Thus, credit supply for micro firms appears to be linked to house prices, whereas credit for small firms is not. Combining these with the relationship between bank failure and firm credit as estimated in Equation 1, Tables 2 and 5 together suggest that micro firm credit varies with real estate collateral prices rather than lending relationship disruptions, and small firm credit is linked to lending relationships rather than collateral values.

These results may be driven by the differences between the sample of all firms and the subsample of firms with linked banks as described above. For example, it may be that small firms which link banks are sensitive to house prices as well as bank failures through being more dependent on external finance or through having more accurate financial records by linked their bank account. To check that this does not drive the results, I run regressions to estimate Equation 5 with the subsample of firms used in estimating Equation 1. The results for this estimation are shown in Panel B of Table 5 and the coefficients are strikingly similar to those for the larger sample. As in Panel A, the association of log credit with house prices remains significant at the 1% level for micro firms at 0.22% change in credit associated with 1% change in the House Price Index (with industry fixed effects) in Column (3) that is significant at the 1% level. In Column (4) with firm fixed effects, a 1% increase in house prices associated with a 0.34% increase in firm credit. In Columns (5) and (6) with small firms, I find that the magnitude of the effects is smaller and is not significant. This suggests that the results are not driven by the selection of firms that link their bank accounts.

Panel C and D rerun the regressions in Panels A and B Columns (1)-(6) for annual frequency data. This is to account for the large number of zeros that can occur in the credit measure, that may be measured better at a more aggregate level. I find that using annual frequency gives similar results. For both the full sample in Panel C and the sample overlapping with the banking sample in Panel D, we find that house prices and credit are positively correlated for micro firms but not for small firms. With industry fixed effects, there is a change of 0.19% in credit associated with a 1% change in house prices for the large sample, and a change of 0.21% credit associated with a 1% change in credit for the sample with linked banks. With firm fixed effects, there is a 0.37% change in micro firm credit in the overall sample and a 0.44% change for the sample with lending relationships. The similarity in coefficients for the overall sample and for the sample of firms with matched banks again support that these two groups are not inherently different in their sensitivity of credit to credit shocks.

The sensitivity of firm credit to house prices are monotonic in firm size but with the reverse trend as seen for the coefficient on bank failure. I plot the coefficients of regressions following the specification in Equation 5 across standard employment bins from the US Census Bureau in Figure 4. The coefficients are for the annual level data and the sparseness of data in the larger bins allows for fixed effects only at NAICS 2 and Year-State levels to control for demand shocks. The graph is indicative of a monotonic relationship between firm credit and house prices, with the positive correlation between $Log(Credit_{it})$ and $Log(HPI_{zt})$ declining with firm size. Controlling for demand shocks, these results suggest that firms at the lower end of the size distribution within the small business universe are more dependent on housing collateral to access credit relative to firms are the higher end of the distribution. Combining this with the results on bank failures, it appears that within the small business universe, moving across firm size implies a shift from the use of personal housing collateral towards the use of lending relationships to access external credit.

5.2 Tradability

Estimation of Equation 5 may still have an omitted variable bias if county-time fixed effects are not sufficient to control for local economic shocks that drive consumer demand and subsequently drive firm credit demand. To check the house price results are robust to this, I focus on tradable sectors where local demand is less relevant for firms. I continue to measure the house price index at the ZIP code of the owner but now consumer demand is more geographically dispersed. The setup follows Adelino *et al.* (2015), where the authors work with the categorisation of industries from Mian & Sufi (2012), who define a 4 digit NAICS industry as tradable if it has the sum of imports and exports to be higher than \$10,000 per employee or exceeding \$500 million[20]. Retail industries, restaurants and grocery are classified as non-tradable. Adelino *et al.* (2015) subsample firms along the spectrum of tradability, removing classes of non-tradable industries from the sample. If credit of firms

[20] See the online appendix of Mian & Sufi (2012) for the classification of tradable industries.

is still positively associated with house prices when non-tradable industries are removed, it suggests a role for the supply of credit through house prices rather than the relationship being entirely demand driven. If the results do not withhold removing non-tradable industries, then we can deduce that the relationship between house prices and credit is driven by demand.

The results for Equation 5 accommodating tradability to separate demand shocks from credit shocks are shown in Table 6. Panel A estimates the equation for quarterly-level data for firms of all sizes, and Panel B for quarterly-level data of micro firms. Column (1) shows the regression of log credit on house prices for firms in all sectors. The fixed effects are also at the year-county or the quarter-county level, In this case, the coefficients are significant for firms of all sizes in Panel A. For micro firms in Panel B, which is the set of firms for which there is a highly significant positive correlation between $Log(Credit_{it})$ and $Log(HPI_{zt})$ as seen in Table 5, we also find the coefficients are highly significant. Moving across to Column (2), where all firms in the construction industry are removed from the sample, the coefficient still remains significant. In Column (3), construction as well as tradable industries are removed, and the relationship between firm credit and the house price index continues to remain significant and similar in magnitude. Finally, in Column (4), the sample is restricted to all firms in manufacturing, which is the most tradable segment of businesses and hence has the largest share of demand originating outside of the local market. There is only a small share of firms in the sample in manufacturing, which may explain why results are weakly significant in Column (4) although with a higher point estimate. Panels C and D repeat the results for annual level frequency and find similar results.

The result from Table 5 and Table 6 suggest that credit supply rather than demand drives the relationship between firm credit and house prices. The differences in coefficients in Table 6 may reflect different requirements for external capital across industries, and thus the magnitudes are not interpretable. The significance of the coefficient in subsample of industries where local demand effects are plausibly lower indicates a role for the credit collateral channel.

6 Additional results

In this section, I include additional results for both banking and housing shocks.

6.1 Sample Selection

We may be concerned that selection into reporting banking relationships is driving the results for the difference in the response of micro and small firm credit to the two shocks. Without distinguishing between micro and small firms, we may expect firms of smaller size to be more sensitive to all credit shocks based on the arguments of Bernanke (1983). A potential concern is that micro firms that report banking relationships are distinct from micro firms that do not report banking relationships, but in such a way that makes them less dependent on banking finance, so as to not have a significant response to bank failure.

Reasons why micro firms may enter into banking relationships typically make them more dependent on credit. For example, if older micro firms have credit histories and are now able to approach borrowers for credit, they will be more likely to report credit relationships but also will be more affected by disruptions in credit supply from banks. The same would hold for micro firms in industries that are more dependent on external credit.

We need to check for micro firms that select into banking relationships for reasons that are not related to higher credit demand. The main driver of this may be easier accounting due to higher transaction volumes. A second reason may be the organisation structure of the firm - for example, owners of limited liability companies do not have their personal assets seized in the event of poor business performance, and thus may be more likely to raise credit from housing assets. Firms with other organisation structures such as corporations or non-profits, may prefer bank credit rather than use personal assets for raising credit.

In Appendix Table A.3 I compare the above-mentioned characteristics for the two samples of firms that report banking relationships and of firms which do not. In the previous section, I also estimate the results of the housing specification on the set of firms which select into banking relationships, and the results are similar in magnitude and significance for the two samples. These results indicate that selection into reporting banking relationships is not driving the results.

6.2 External Dependence on Finance

Firms which have higher dependence on external sources of financing may be affected more by credit supply shocks. To study this, I use the measure of external dependence on finance developed by Rajan & Zingales (1998). The measure is defined as capital expenditures minus cash flow from operations divided by capital expenditures, using Compustat firms in the US. The ratio is aggregated across firms and over time (across the 1980's), to develop an industry-level measure. Using large listed firms has a key advantage. Publicly listed firms are typically mature and less financially constrained, whereas a similar measure constructed for small firms may have an identification problem in determining the technology of external finance at an industry level. Haltenhof *et al.* (2014) describe this endogeneity concern with the example that a given industry's low dependence on bank loans could simply indicate financing constraints[21].

To study how external financing interacts with the impact of credit supply shocks, I estimate Equations 1 and 5 for the subsample of firms that are in the top and bottom quartiles of the external dependence measure based on Rajan & Zingales (1998) for both credit shocks[22]. The results are shown in Appendix Table A.4. Firms which are in industries that are above median in the dependence on external finance are affected more, whereas those which are in industries with below median external dependence on finance are affected less and in fact the impact is not significant. These results are amplified when subsampling small firms, which are more sensitive to bank failures.

6.3 Firm Revenue

In this section, I study the relationship between firm credit and revenue and identify the role of credit supply shocks on bank credit. An Ordinary Least Squares estimation of the relationship between firm revenue and credit raises endogeneity concerns. There may be omitted factors that drive firm revenue and firm credit, which will bias the OLS estimate of β. The instrumental variables approach aims to identify the role of shocks to credit supply on firm revenue. The unique advantage of my dataset is that it reports firm credit for small businesses, allowing me to overcome this issue. I do this through Two Stage Least Squares estimation, where the first stage uses Equations 1 or 5, and the second stage is the relationship between firm revenue and firm credit:

$$Log(Rev_{it}) = \beta Log(Credit_{it}) + \theta_{tc} + f_i + e_{it} \tag{6}$$

where $Log(Credit_{it})$ is the fitted value from the first stage in the IV regression. $Log(Rev_{it})$ is constructed by aggregating all transactions that are positive transfers to the firm and categorised as Income or Other Income, and the set of controls are fixed effects at the Quarter-County and the NAICS 2 level, as in the first stage regressions for the relationship between firm credit with banking and housing shocks.

Appendix Table A.5 shows OLS and IV estimation for equation A.5. Column (1) and Column (3) show the coefficient from the OLS estimation of $Log(Rev_{it})$ on $Log(Credit_{it})$. There is a strong positive correlation between firm revenue and credit which is slightly higher

[21] Cetorelli & Strahan (2006) argue that the Rajan Zingales measures provides a powerful instrument for small firms' demand for bank credit, whereas a direct measure of dependence on bank credit using bank loans to assets ratios of small businesses does not.

[22] The original measure is based on SIC 2 digit codes. I convert SIC 2 digit industry codes to NAICS 2 digit industry codes using the Census crosswalk for 1997. To deal with many to many matching of SIC to NAICS codes, I take each SIC 2 for which I have the measure of external dependence, and assign the measure to all NAICS 2 it corresponds to in the crosswalk. I drop the NAICS that match to multiple SIC codes.

for micro firms. A 1% change in firm credit is associated with a 0.2% increase in revenue for micro firms and 0.17% for small firms. This does not identify the role of credit supply for firm revenue. I identify the role of credit supply by using shocks to credit supply through bank failures and house price shocks for micro and small firms.

Column (2) shows the first stage for housing shocks for micro firms and Column (4) shows the first stage for banking shocks for small firms, with the F-statistic of the two-step procedure given below[23]. Consistent with Table 5, the first stage for the house price instrument is strong with an F-statistic of 342 for micro firms in Column (2). Consistent with Table 2, the first stage for the banking instrument is strong for small firms, with an F-statistic of 35 in Column (4).

Using instruments that satisfy the inclusion restriction for micro and small firms, I estimate equation A.5. In Column (2), I instrument firm credit using the log of the House Price Index for micro firms to estimate the response of revenue to credit supply. The relationship between revenue and credit remains positive and significant, with a coefficient of 0.29 for the regression of $Log(Rev_{it})$ on $Log(Credit_{it})$. In Column (4), I instrument firm credit for small firms using bank failures to identify the relationship between credit supply and revenue. This yields a coefficient of 0.32 which is significant at the 1% level.

The coefficient using instrumental variables is larger than the OLS coefficient for both micro and small firms. An omitted variable that is negatively correlated with the outcome of firm revenue can cause the OLS coefficient to be downward biased compared to the IV[24]. The exclusion restriction may not be satisfied and the magnitudes in this case may be biased. The results suggest a role of credit supply for firm revenue, but the coefficients may not reflect true sensitivities.

7 Conclusion

This paper uses a new dataset on small business financials to study small business financing during the Great Recession. I show shocks in the banking sector and the real estate market matter for small business credit. I find that bank failures are associated with a 25% decline in firm credit, and this is driven by small firms. Micro firm credit does not decline with failure of a bank associated with the firm. The relationship between firm credit and bank failure is monotonically increasing in firm size. The response of firm credit to bank failure is temporary, and is higher when the firm has fewer banking relationships and also increases

[23] The sample used in the first stage is set to match the IV sample. The coefficients for the regressions of $Log(Credit_{it})$ on banking and housing shocks remain similar to those in Tables 2 and 5.

[24] Omitted demand is more likely to be positively correlated with firm revenue, driving the bias in the opposite direction.

with the length of the relationship with the failed bank. Examining the role of house price movements for firm credit, I find the relationship between house prices and firm credit is significant for micro firms, with a 1% change in house prices associated with 0.2-0.5% change in firm credit. This relationship *declines* with firm size and is not significant for small firms. I also show that revenue decreases with negative shocks to credit supply, suggesting that financing matters for performance.

These results provide insights into how firms in the small business universe overcome information asymmetries. They suggest that micro firms use personal housing collateral to borrow from banks while small firms develop lending relationships with banks. The robustness of the results to age controls indicate that banks screen firms on the basis of size, rather than only on past business performance or credit history which are associated with age. This can be understood in a framework where firms have different demands for credit and banks have fixed costs as a function of loan size.

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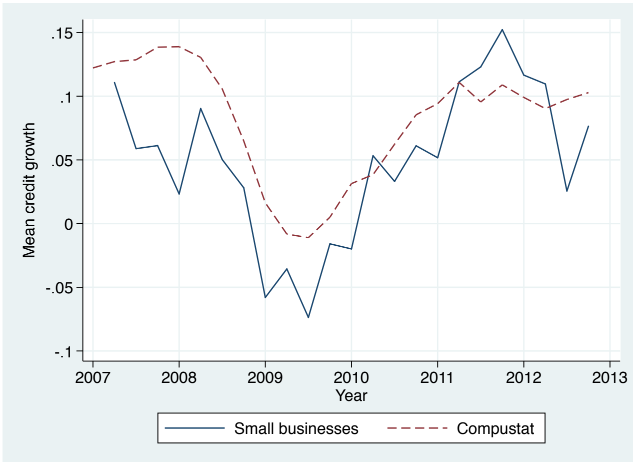
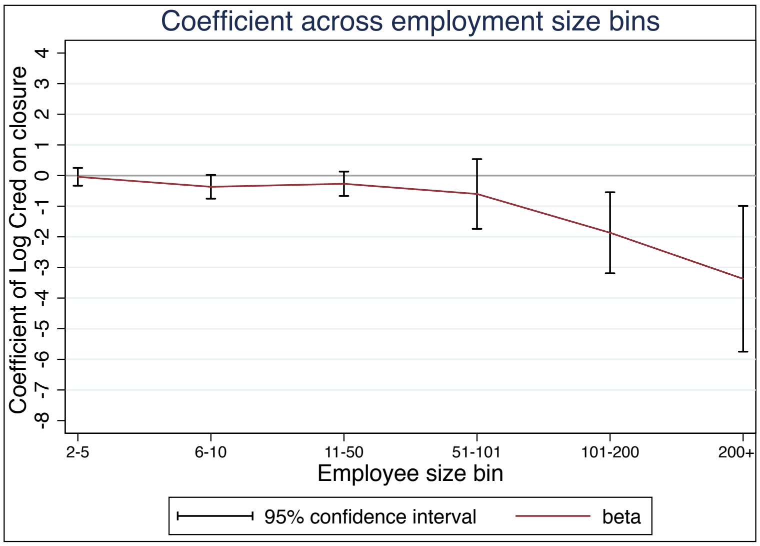
Figures and Tables

Figure 1: Credit Growth Over the Business Cycle



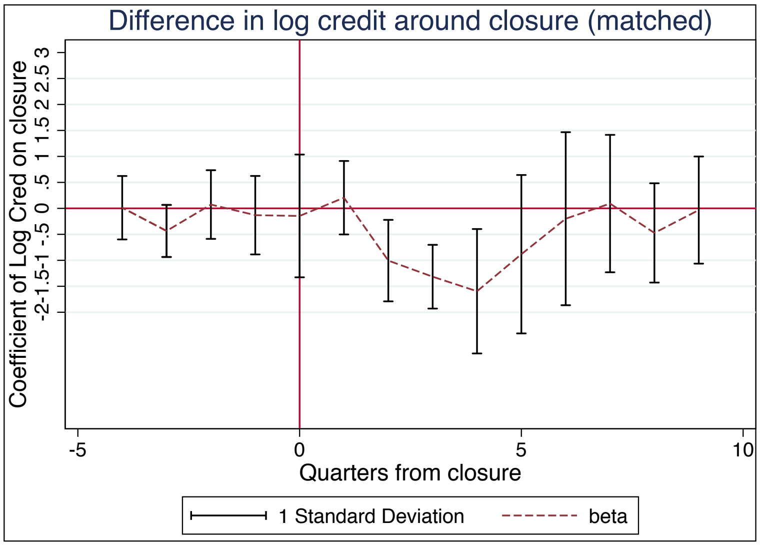
Notes. Annual QoQ growth in average total liabilities for small businesses in the sample and Compustat firms. Both firm-level datasets are filtered to keep only firms with at least 4 quarters of data and a moving average of three quarters taken over growth. Sample data is restricted to positive values of long-term liabilities for firm-quarters and winsorised at the 1% level.

Figure 2: Log Credit and Bank Failure Across Firm Size



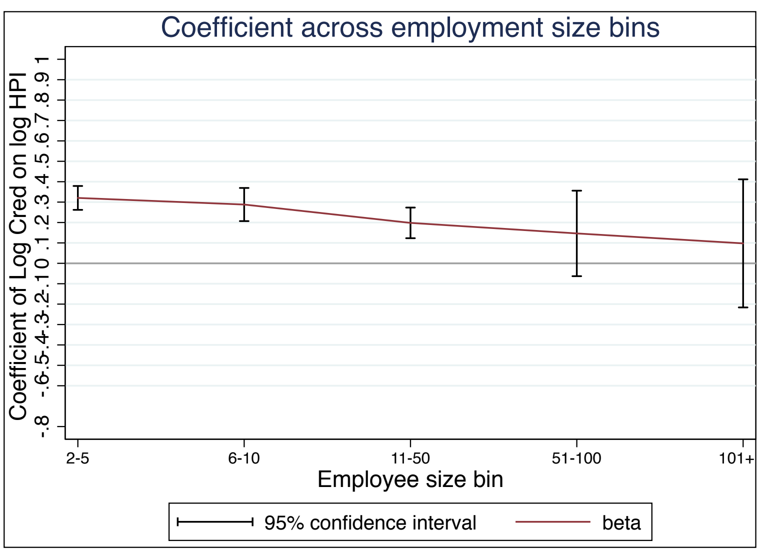
Notes. Correlation of firm credit to bank failures across firm size. The x-axis is based on standard size categories followed by the US Census Bureau and the y-axis is the coefficient of the regression with dependent variable log credit and independent variable a dummy that equals 1 if the firm is impacted by bank closure in the current or the previous year. Fixed effects are at the NAICS 2 and Year-State levels. Standard errors are clustered at the firm level.

Figure 3: Matching and Event Study



Notes. Difference between log credit around bank closure of small firms whose banks failed and matched firms whose banks did not fail. Firms matched using propensity score based on 2 digit NAICS, state, log employment and log age a year before closure, with one match per affected firm and calliper for propensity score 0.01. Standard errors are bootstrapped with 500 draws from the sample.

Figure 4: Log Credit and House Prices Across Firm Size



Notes. Correlation of firm credit with house price index across firm size. The x-axis is based on standard size categories followed by the US Census Bureau and the y-axis is the coefficient of the regression with dependent variable log credit and independent variable the ZIP code level house price index measured at the owner's address. Fixed effects are at the NAICS 2 and Year-State levels. Standard errors are clustered at the firm level.

Table 1: Summary Statistics

	Mean	Std.Dev	Min	Max	Median
Small businesses					
Size (employees)	11.92	37.13	0	5103	3
Revenue ($)	1,557,643	430,244,608	0	9,570,071	317,640
Credit ($)	62,521	6,943,580	0	842,454	0
Credit ($) >0	335,579	16,083,934	40	4,053,002	4,053,002
Micro firms					
Size (employees)	2.72	2.54	0	9	2
Revenue ($)	872,260	55,399,336	0	7,040,920	228,486
Credit ($)	55,375	8,097,182	0	652,750	0
Credit ($) >0	347,510	20,281,938	43	3,919,374	35,328
Small firms					
Size (employees)	36.59	65.00	10	255	20
Revenue ($)	3,396,628	820,702,464	0	14,115,132	715,018
Credit ($)	81,695	1,287,384	0	1,299,130	0
Credit ($) >0	315,857	2,516,734	35	4,321,989	46,262
Compustat firms					
Size (employees)	7468.34	21215.08	0	145500	623
Revenue (million $)	2802.01	9166.25	0	67052	184.95

Notes. The sample consists of 844,882 firm-year observations for the 141,678 firms in the sample. Employment numbers are taken to be the March numbers, else subsequent or previous months if March data missing. Credit is all new long-term liabilities issued. All variables are winsorised at the 1% level

Table 2: Firm Credit Response to Bank Failure

	Credit					
	All	All	Micro	Micro	Small	Small
	(1)	(2)	(3)	(4)	(5)	(6)
A: Log credit						
Bank Failure	-0.606***	-0.296***	-0.192	0.005	-0.716***	-0.361***
	(0.170)	(0.099)	(0.127)	(0.091)	(0.220)	(0.129)
Firm-Quarters	235,790	235,790	135,253	135,253	100,537	100,537
B: Log credit						
Bank Failure	-0.764***	-0.563***	-0.072	-0.061	-0.906***	-0.716***
	(0.225)	(0.177)	(0.129)	(0.133)	(0.288)	(0.228)
Firm-Years	84,657	84,657	51,764	51,764	32,893	32,893
C: Log(Credit/Sales)						
Bank Failure	-0.566**	-0.616***	-0.171	-0.229	-0.650**	-0.658***
	(0.247)	(0.193)	(0.160)	(0.198)	(0.304)	(0.243)
Firm-Years	67,470	67,470	38,925	38,925	28,545	28,545
D: Credit growth						
Bank Failure	-0.284**	-0.344**	0.074	0.223	-0.367***	-0.446**
	(0.117)	(0.159)	(0.111)	(0.175)	(0.141)	(0.195)
Firm-Years	40,424	40,424	20,694	20,694	19,730	19,730
Time-County	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2	Yes		Yes		Yes	
Firm		Yes		Yes		Yes

Notes. The independent variable takes value 1 for the quarter the firm faces bank failure and the following 6 quarters in Panel A. It takes value 1 for the year of bank failure and the following year in Panels B-D. It The sample is all firms with linked banks. Columns (1) and (2) is the sample of firms of all sizes, columns (3) and (4) is restricted to micro firms (with less than 10 employees), columns (5) and (6) is small firms (which have more than 10 employees). Credit is measured as the sum of all transactions categorised as long-term liabilities to a firm. In Panel (A) and (B), the dependent variable is Log(Credit), in Panel (C) it is Log(Credit/Revenue) and in Panel (D) it is credit growth, defined calculated as $0.5 \cdot (credit_t - credit_{t-1})/(credit_t + credit_{t-1})$. County-Time is County-Quarter in Panel (A) and County-Year in Panels (B)-(D). Dependent variables are winsorised at the top and bottom 1%. Regressions are weighted by employment. All standard errors are clustered at the firm level.

Table 3: Selection Effects

(a) Balance in 2006

Variable	Failure	No failure	Diff. p-value (Raw)	Diff. p-value (with FE's)
Credit	61,401	51,166	0.284	0.174
Log(Credit)	10.42	10.36	0.727	0.965
Log(Credit/Sales)	-2.57	-2.89	0.072	0.116
Employment	12.26	12.54	0.819	0.695
Log Employment	1.86	1.95	0.145	0.322

(b) Placebo Test: Six Quarters Before Bank Failure

	Log(Credit)					
	All	All	Micro	Micro	Small	Small
	(1)	(2)	(3)	(4)	(5)	(6)
Bank Failure - 6 qtrs	-0.110	0.069	-0.147	-0.040	-0.102	0.098
	(0.188)	(0.116)	(0.153)	(0.098)	(0.228)	(0.144)
Firm-Qtr Obs	137,133	137,133	65,717	65,717	71,416	71,416
Qtr-County	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2	Yes		Yes		Yes	
Firm		Yes		Yes		Yes

(c) Placebo Test: Six Quarters After Bank Failure

	Log(Credit)					
	All	All	Micro	Micro	Small	Small
	(1)	(2)	(3)	(4)	(5)	(6)
Bank Failure + 6 qtrs	-0.353*	0.053	0.013	-0.084	-0.410*	0.075
	(0.182)	(0.140)	(0.154)	(0.120)	(0.242)	(0.190)
Firm-Qtr Obs	118,806	118,806	67,330	67,330	51,476	51,476
Qtr-County	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2	Yes		Yes		Yes	
Firm		Yes		Yes		Yes

Notes. Panel (a) shows balancing tests for firms that faced bank failures and firms which did not. Panel (b) shows a placebo test for the response of firm credit to bank closure measured six quarters before bank failure, and Panel (c) shows the placebo for six quarters after the bank failure. Regressions are shown for the entire sample as well as split into micro and small firms. The dependent variable is the log of credit determined by aggregating all transactions which are long-term liabilities to the firm, and winsorised at the top and bottom 1%. All regressions are weighted by the number of employees. Standard errors are clustered at the firm level.

Table 4: Heterogeneity of Firm Credit and Bank Failure

(a) Panel A: Heterogeneity by Number of Banks

	Log Credit					
	All			Small		
	1 bank	2 banks	3-5 banks	1 bank	2 banks	3-5 banks
Bank Failure	-0.646***	-0.485***	-0.203	-0.758***	-0.562***	-0.202
	(0.110)	(0.129)	(0.148)	(0.142)	(0.166)	(0.188)
Obs	234,274	231,923	231,065	99,806	99,011	98,666
Qtr-County	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2	Yes	Yes	Yes	Yes	Yes	Yes

(b) Panel B: Heterogeneity by Length of Lending Relationship

	Log Credit					
	All			Small		
	All	> Median	> Mean	All	> Median	> Mean
Bank Failure	-0.298***	-0.333***	-0.359***	-0.358***	-0.413***	-0.389***
	(0.087)	(0.102)	(0.106)	(0.114)	(0.133)	(0.130)
Obs	235,790	233,793	233,413	100,537	99,671	99,799
Qtr-County	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes

Notes. Bank failure is a dummy that equals 1 for the quarter the firm faces bank failure and the following 6 quarters. The sample is all firms with banks linked to their account. Credit is measured as the sum of all transactions categorised as long-term liabilities to a firm. In Panel A: Columns (1)-(3) is for firms of all sizes and columns (4)-(6) selects small firms (more than 10 employees). The sample is further split into whether firms experiencing bank failure had 1 , 2, and 3 or more banking relationships at the time of closure in columns (1) and (4), (2) and (5) and (3) and (6) respectively. In Panel (B) Columns (1)-(3) is for firms of all sizes and columns (4)-(6) selects small firms (more than 10 employees). The sample is further stratified to select firms experiencing bank failure had relationships with the failing banks above the median and mean length of bank relationships of the set of firms that experience bank failure. Columns (1) and (3) are all firms, columns (2) and (4) have above median length of a lending relationship and columns (3) and (6) have above mean length of a lending relationship. Log credit is winsorised at the top and bottom 1%. Regressions are weighted by employment. Standard errors are robust.

Table 5: Firm Credit and House Prices

	Log Credit					
	All	All	Micro	Micro	Small	Small
	(1)	(2)	(3)	(4)	(5)	(6)
A. Quarterly -All						
Log HPI	0.091*	-0.083	0.222***	0.330***	0.083	0.260*
	(0.055)	(0.185)	(0.031)	(0.087)	(0.065)	(0.148)
Observations	448,877	448,877	245,520	245,520	203,357	203,357
B. Quarterly - Banking						
Log HPI	0.090	-0.043	0.225***	0.339***	0.083	0.281*
	(0.055)	(0.185)	(0.031)	(0.087)	(0.065)	(0.151)
Observations	448,866	448,866	245,522	245,522	203,344	203,344
C. Annual - All						
Log HPI	0.093*	0.422***	0.189***	0.371***	0.087	0.428**
	(0.050)	(0.146)	(0.037)	(0.143)	(0.059)	(0.169)
Observations	101,913	101,913	55,431	55,431	46,482	46,482
D. Annual - Banking						
Log HPI	0.051	0.190	0.208***	0.439**	0.034	0.160
	(0.066)	(0.222)	(0.048)	(0.207)	(0.082)	(0.267)
Observations	52,979	52,979	30,923	30,923	22,056	22,056
Time-County	Yes		Yes		Yes	
NAICS2	Yes		Yes		Yes	
Time		Yes		Yes		Yes
County		Yes		Yes		Yes
Firm		Yes		Yes		Yes

Notes.. The correlation between firm credit and house prices. The dependent variable is the log of credit determined by aggregating all transactions which are long-term liabilities to the firm, and winsorised at the top and bottom 1%. Columns (1) and (2) is the sample of firms of all sizes, columns (3) and (4) is restricted to micro firms (with less than 10 employees), columns (5) and (6) is small firms (which have more than 10 employees). Panel (A) and Panel (B) are at the annual level and Panel (C) and (D) are at the quarterly level. Panel (A) and (C) have all firms and Panel (B) and (D) are the firms for which bank accounts are linked. Standard errors are clustered at the firm level.

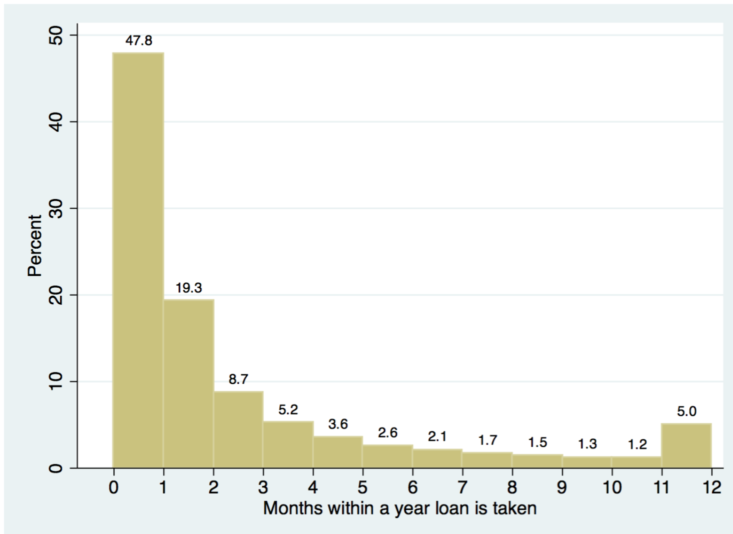
Table 6: Tradability and House Prices

	Log Credit			
	All	All-Constrn	All -Constrn - NonTrad	Manuf
	(1)	(2)	(3)	(4)
Quarterly - all sizes				
Log HPI	0.165***	0.171***	0.176***	0.182
	(0.023)	(0.024)	(0.025)	(0.128)
Observations	448,877	401,785	367,345	22,930
Quarterly - micro firms				
Log HPI	0.211***	0.220***	0.216***	0.171
	(0.027)	(0.029)	(0.030)	(0.142)
Observations	259,742	233,776	214,359	17,929
Annual - all sizes				
Log HPI	0.160***	0.184***	0.195***	0.325**
	(0.026)	(0.029)	(0.031)	(0.141)
Observations	101,913	89,907	81,722	6,477
Annual - micro firms				
Log HPI	0.199***	0.229***	0.227***	0.337*
	(0.033)	(0.035)	(0.037)	(0.174)
Observations	58,651	52,019	47,441	3,752
County-Time	Yes	Yes	Yes	Yes
NAICS2	Yes	Yes	Yes	Yes

Notes.. The regression of log credit on log of the house price index categorised by tradability. The tradable industries categorisation follows the online appendix of Mian & Sufi (2012). Column (1) is all industries, column (2) excludes construction, column (3) excludes construction and non-tradables (retail sector, restaurant and grocery), column (4) is the subset of manufacturing firms. Panel (A) and Panel (B) are at the annual level and Panel (C) and (D) are at the quarterly level. Panel (A) and (C) have firms of all sizes and Panel (B) and (D) are micro firms. Standard errors are clustered at the firm level.

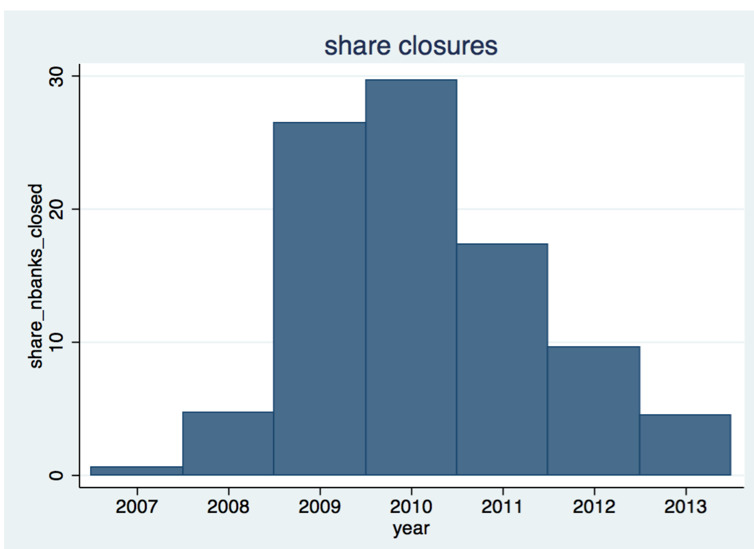
A Additional Figures and Tables

Figure A.1: Frequency of Borrowing



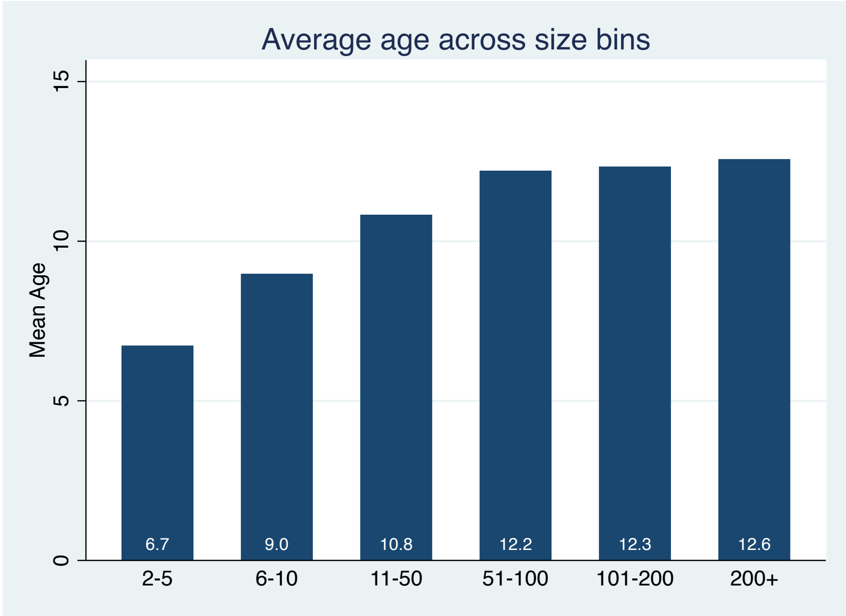
Notes. Number of months in a year that firms borrow. The sample is for 141,678 firms restricted to those with at least one year of borrowing in the dataset.

Figure A.2: Bank Failures During 2007-2013



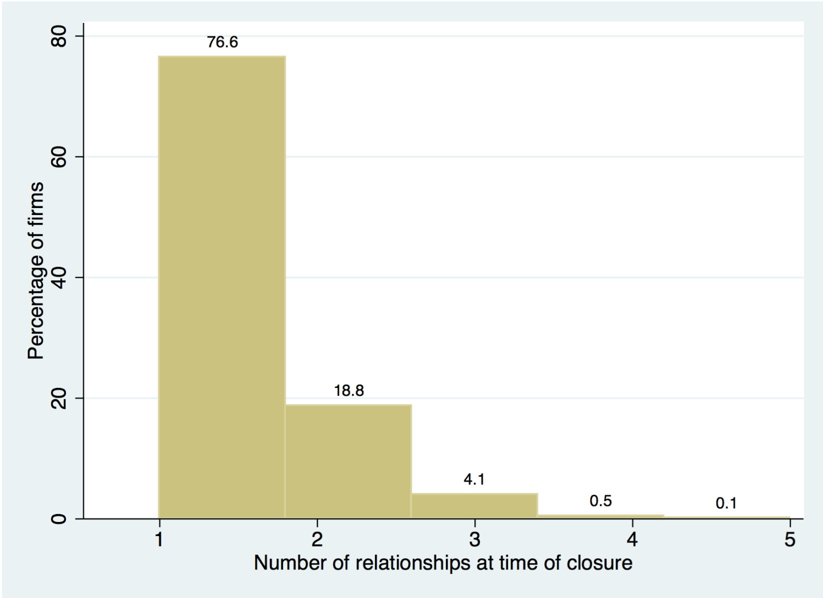
Notes. Bank failures during 2007-2013. Source: Federal Deposit Insurance Corporation.

Figure A.3: Size and Age



Notes. Average age for firms in different size bins. Standard size bins as used by the US Census Bureau.

Figure A.4: Number of Banking Relationships



Notes. Number of banking relationships at the time of failure for firms which experienced bank failure.

Table A.1: Firm Credit and Bank Failure - Robustness

	Credit					
	All	All	Micro	Micro	Small	Small
	(1)	(2)	(3)	(4)	(5)	(6)
A. Cutoff = 5						
Bank Failure	-0.606***	-0.296***	-0.149	0.052	-0.641***	-0.316***
	(0.170)	(0.099)	(0.128)	(0.116)	(0.186)	(0.108)
Firm-Qtr Obs	235,790	235,790	74,705	74,705	161,085	161,085
B. Cutoff = 15						
Bank Failure	-0.606***	-0.296***	-0.241**	-0.135	-0.746***	-0.382***
	(0.170)	(0.099)	(0.116)	(0.083)	(0.253)	(0.148)
Firm-Qtr Obs	235,790	235,790	166,019	166,019	69,771	69,771
C. Lag Size						
Bank Failure	-0.606***	-0.296***	-0.183	0.049	-0.711***	-0.383***
	(0.170)	(0.099)	(0.130)	(0.092)	(0.219)	(0.129)
Firm-Qtr Obs	235,790	235,790	118,862	118,862	116,928	116,928
D. Firm Age						
Bank Failure	-0.626***	-0.305***	-0.185	-0.013	-0.739***	-0.372***
	(0.173)	(0.101)	(0.131)	(0.094)	(0.222)	(0.131)
Log Age	-0.087***	0.046	-0.110***	0.101**	-0.142***	0.025
	(0.024)	(0.063)	(0.016)	(0.045)	(0.032)	(0.089)
Firm-Qtr Obs	224,827	224,827	125,958	125,958	98,869	98,869
Qtr-County	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2	Yes		Yes		Yes	
Firm		Yes		Yes		Yes

Notes. Bank failure is a dummy that equals 1 for the quarter the firm faces bank failure and the following 6 quarters. The sample is all firms with banks linked to their account. Columns (1) and (2) is the sample of firms of all sizes, columns (3) and (4) is restricted to micro firms (with less than 10 employees), columns (5) and (6) is small firms (which have more than 10 employees). Credit is measured as the sum of all transactions categorised as long-term liabilities to a firm. In Panel (A), the cutoff for micro vs. small firms is changed to 5 and in Panel (B) the cutoff is changed to 15. In Panel (C) the cutoff for micro vs. small firms is based on employment 2 years prior to bank failure. In Panel (D) firm age measured as the difference in years between the current year and the minimum of the first year of business recorded in Dun and Bradstreet of the firm and the registration date of the firm in the software. The dependent variable Log credit is winsorised at the top and bottom 1%. Regressions are weighted by employment. All standard errors are clustered at the firm level.

Table A.2: Exit Following Bank Failure

	Exit					
	All	All	Micro	Micro	Small	Small
	(1)	(2)	(3)	(4)	(5)	(6)
Bank Failure	0.010	0.006	0.001	-0.006	0.012	0.011
	(0.007)	(0.008)	(0.003)	(0.007)	(0.009)	(0.010)
Firm-Yr Observations	232,004	232,004	152,760	152,760	79,244	79,244
Year-County	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2	Yes		Yes		Yes	
Firm		Yes		Yes		Yes

Notes.. Exits defined at the annual level using DUNS data.

Table A.3: Sample Selection

	All		Micro		Small	
Sample:	HP	Bank	HP	Bank	HP	Bank
Age:						
Mean	10.03	8.38	8.43	7.14	12.46	10.56
Median	6	5	5	4	8	7
Ownership type:						
C-corporation	12.02	11.27	11.51	10.85	11.79	11.19
S-corporation	16.75	15.36	15.94	14.87	16.02	14.64
LLC	11.65	11.17	11.93	11.51	11.15	10.63
Sole proprietor	10.21	12.17	11.78	13.25	9.60	11.18
Non-Profit	2.87	2.88	2.49	2.62	3.27	3.22
Unclassifed	1.01	1.25	1.15	1.57	0.99	1.16
Other	40.68	40.11	39.61	39.24	41.57	41.24
Not reported	4.79	5.79	5.58	6.30	5.62	6.75
Sector:						
Agriculture	1.32	0.88	1.10	0.77	1.58	1.09
Construction	8.58	8.25	8.22	8.22	8.99	8.29
Manufacturing	5.18	4.12	5.05	4.14	5.34	4.08
Mining	0.29	0.16	0.24	0.15	0.36	0.17
Retail	7.93	7.18	7.83	7.01	8.05	7.48
Service	72.37	75.67	72.75	75.71	71.92	75.60
Wholesale	4.32	3.75	4.80	4.01	3.76	3.28

Notes. Comparison of samples used in house price and bank failure specifications (quarterly samples).

Table A.4: External Dependence on Finance

	Log Credit			
	(1)	(2)	(3)	(4)
A. Bank Failure	All		Small	
Ext. Dependence:	Low	High	Low	High
Bank failure	-0.209	-0.511***	-0.312	-0.601***
	(0.872)	(0.162)	(1.074)	(0.213)
Observations	25,044	210,746	13,311	87,226
B. House Prices	All		Micro	
Ext. Dependence:	Low	High	Low	High
Log HPI	0.154**	0.172***	0.166	0.217***
	(0.068)	(0.025)	(0.108)	(0.029)
Observations	50,186	398,754	22,331	223,172

Notes.. External dependence on finance and the impact of credit shocks. Low and high external dependence on finance are defined as the top and bottom quartiles of the industry-level measure developed by Rajan & Zingales (1998). Bank failure is a dummy that equals 1 for the quarter the firm faces bank failure and the following 6 quarters. House price measure is log of the Zillow monthly index at the ZIP code of the owner's address, averaged over months in a quarter. The sample in Panel B is all firms with address information of the owner and in Panel B A is restricted to the firms with bank linkages. Regressions in Panel A are weighted by employment. Credit is measured as the sum of all transactions categorised as long-term liabilities to a firm. County-Quarter 2 digit NAICS fixed effects are used throughout. Standard errors are clustered at the firm level.

Table A.5: Firm Revenue and Credit

	Log(Revenue)			
	Micro		Small	
	OLS	IV House	OLS	IV Bank
	(1)	(2)	(4)	(5)
Log(Credit)	0.193***	0.290***	0.168***	0.320***
	(0.001)	(0.034)	(0.003)	(0.105)
First Stage:				
Bank Failure or Log(HPI)		0.225***		-0.704***
		(0.012)		-0.119
Observations	319,052	242,610	98,542	98,542
F-statistic		341.75		35.07

Notes. Relationship between revenue and credit instrumented using bank failures and house prices. Dependent variable is Log Revenue at the firm level. Independent variable is Log Credit. Bank failure is a dummy equalling 1 for the quarter the firm faces bank failure and the following 6 quarters. The sample is all firms with linked bank accounts. Credit is the sum of all transactions categorised as long-term liabilities to a firm. Log(Credit) and Log(Revenue) are winsorised at the top and bottom 1%. All regressions have been weighted by the number of employees. Standard errors are robust.

B Data Appendix

B.1 Representativeness

Table A.6: Representativeness Across Firm Size

Firm Employment	Share (population)	Share (Sample)
0-4	61.89	49.14
5-9	17.34	19.24
10-14	6.82	9.39
15-19	3.54	5.55
20-24	2.17	3.65
25-49	5.78	7.42
50-99	1.31	3.59
100+	1.14	1.94

Notes. Mid-March employment shares in the population and the sample for 2010. Population statistics are sourced from the Statistics of U.S. Businesses published by the Census Bureau (total number of firms is 5,734,538). The number of employees is sourced from the records documenting hiring and release dates of employees for 2010 (total number of firms is 76,918).

Table A.7: Representativeness Across Firm Age

Age (years)	Share (Census)	Share (Sample)
0	8.93	1.51
1	6.67	7.97
2	5.50	10.87
3	5.13	8.18
4	5.29	7.99
5	4.96	7.99
6-10	20.17	25.25
11-15	14.04	12.09
16-20	10.05	6.02
21-25	7.91	3.69
26+	11.36	8.43

Notes. Comparison of population for 2012 from Business Dynamics Statistics and the sample for 2012 March on age, with 4,577,659 firms in the population and 91,571 in the population.

Table A.8: Representativeness Across Sectors

Sector	Share (population)	Share (Sample)
Service	70.91	77.00
Retail	11.97	7.85
Construction	11.44	9.01
Manufacturing	4.87	4.68
Mining	0.43	0.24
Agriculture	0.38	1.19

Notes. Distribution of firms across 1 digit NAICS Sectors for March 2010. Population statistics from the Statistics of U.S. Businesses, US Census Bureau. The total number of firms is 5,734,538. Sample data uses the industry from matching to Dun and Bradstreet for 76,918 firms in 2010. Firms under "Unclassified" and "Public Administration" have been removed.

Table A.9: Representativeness Across Industries

Industry	Share (population)	Share (Sample)
Professional services	14.14	22.75
Retail trade	11.97	7.85
Other services	11.96	5.11
Health care	11.50	11.23
Construction	11.44	9.01
Accommodation and food	8.94	4.84
Waste management	6.03	12.95
Real estate	4.93	3.41
Manufacturing	4.87	4.68
Finance	4.45	4.01
Transportation	3.22	2.80
Arts and recreation	2.07	2.66
Education	1.54	2.90
Information	1.41	3.95
Management	0.6	0.26
Mining	0.43	0.24
Agriculture	0.38	1.19
Utilities	0.12	0.13

Notes. Distribution of firms across 2 digit NAICS Industries for March 2010. Population statistics from the Statistics of U.S. Businesses, US Census Bureau. The total number of firms is 5,779,427. Sample data uses the industry from matching to Dun and Bradstreet for 76,837 firms in 2010. Firms under "Unclassified" and "Public Administration" have been removed.