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.

1 Introduction

Small businesses face financial constraints due to asymmetric information in lending markets, which may be amplified during periods of economic contraction (Stiglitz and Weiss, 1981; Bernanke, Gertler, and Gilchrist, 1994). Financially constrained small businesses are more sensitive to economic shocks and drive aggregate dynamics (Bernanke, 1983). Two widely-documented ways in which these firms overcome financial constraints are (1) by establishing

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lending relationships with banks, and (2) by using collateral. Lending relationships allow small, non-transparent firms to share information with banks and enable access to credit (Petersen and Rajan, 1994; Berger and Udell, 1995; Cole, 1998). Firms may face tighter credit constraints when banks fail, loan officers move, and information about the firm is lost (Brewer III et al., 2003; Drexler and Schoar, 2014). Personal housing collateral of the business owner can be pledged for business loans (Robb and Robinson, 2014; Corradin and Popov, 2015; Hurst and Lusardi, 2004), and business owners can access top-up credit as the value of the collateral rises. Large fluctuations in house prices thus affect the ability of small business owners to access credit. The cost of acquiring information for the relationship channel varies across firm size (Scott, 2006), which can create heterogeneity within the small business universe in how firms overcome asymmetric information.

Consider two categories of small businesses based on the US Bureau of Labor Statistics nomenclature: "micro firms" - firms less than 10 employees, and "small firms" - small businesses with more than 10 employees. For smaller loan volumes demanded by micro firms, 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 basis for lending. If this is the case, movements in real estate prices will matter for micro firms. Banking shocks will matter less, given micro firms do not depend on lending relationships that may get disrupted in banking shocks. For small firms who borrow based on lending relationships, there may be frictions associated with banking shocks that lead to declines in credit, but these firms may be less affected by movements in the price of collateral as they are not as dependent on collateral for credit.

Previous research has emphasised the role of real-estate collateral[1] and declining bank credit[2], but studies have been limited by data constraints in three ways. First, there is no

[1] Schmalz et al. (2013) and Adelino et al. (2015) find a relation between housing collateral and firm dynamics for the US during the Great Recession, while Kerr et al. (2015) study the impact of house prices on entrepreneurship in 2000-2004. Chaney and Sraer (2012) measure firms' real estate assets and use MSA level house prices movements in the 1993-2007 period. Bahaj et al. (2016) and Kleiner (2014) study the collateral channel for the UK and Gan (2007) looks at corporate collateral in Japan.

[2] Greenstone et al. (2014), Chodorow-Reich (2014) and Nguyen (2014) study various types of banking shocks for the US and the impact on employment finding differing results. Bentolila et al. (2013) find declines in employment linked to declining bank health for Spain while Berton et al. (2018) find the same for Italy. Amiti and Weinstein (2013) and Gibson (1995) find investment declines for Japanse firms linked to banking shocks. Ongena et al. (2003) find declining fim equity value following banking shocks for Norway, Yamori and Murakami (1999) find stock return declines following bank failure in Japan, Joeveer et al. (2004)

readily-available data source for financials of small businesses in the US. 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.

Given data constraints, existing work is limited to looking at firm-level measures for larger firms or aggregated measures of real outcomes for small ones. 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. Chodorow-Reich (2014) finds large employment effects on firms following breakdown of lending relationships for firms who were borrowing from banks linked to Lehman Brothers. These firms, which borrowed through the syndicated loan market, are typically larger than the representative firm in the population[3]. Turning to firm-level collateral price shocks for large firms, Chaney and Sraer (2012) find that real estate collateral matters for the credit of publicly-listed firms. Small-firm studies for housing and banking shocks use Census data which is representative but which does not capture financial variables for the Recession years. Greenstone et al. (2014) use shocks to banking supply using changes in local composition of national banks to find that small businesses credit supply declines with negative banking shocks, but the employment effects from this channel are small. Nguyen (2014) studies the impact of bank branch closings on small businesses using Census tract data and shows that lender-specific relationships matter once broken are hard to rebuild. Adelino et al. (2015) use County Business Patterns data published by the US Census Bureau covering a representative sample of US firms. They find that the housing collateral channel drives small businesses entry and exit dynamics. Gertler and Gilchrist (2018) examine the impact of both housing collateral and banking distress using quarterly state-level data and find that both credit shocks are important for employment. The lack of direct measures of credit is a limiting features of these studies. In the Great Recession, small business credit growth declined more than that of large, publicly-listed firms, as shown in Figure 1.

Using a novel dataset sourced from the leading online accounting software in the United

show a decline in survival rates of firms affected by bank failure in Estonia while Bae et al. (2002) find firm value declining with banking shocks for Korean firms.

[3]The median firm size in the study is 620 employees, with the 10th percentile 77 employees. For comparison, the size distribution of firms from the Statistics of Small Businesses (SUSB) published by the US Census is shown for 2010 in Table B.1.

States, I develop measures for banking and housing collateral shocks at the firm level for small businesses, and thus build a clearer picture of the role of these two types of credit shocks in the Great Recession. 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 bookkeeping. 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, who is responsible for the restructuring and shutdown 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 in this segment of firms.

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, includingdistinguishing 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 about 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 result is robust to estimating the effect only for tradables, where demand effects are lower. This is consistent with micro firms using collateral to overcome asymmetric information, which holds true if banks are unwilling to undergo costs of acquiring information for these firms.

The differential impact of banking and housing shocks on micro and small firms 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.

This paper links to multiple strands of literature. It contributes to the literature measuring the impact of credit shocks effects on small businesses during the Great Recession in the US, through directly measuring credit outcomes and two key shocks to small businesses at the firm-level during this period. In addition to this, the paper also provides micro-level evidence for the broader literature that models the transmission of financial shocks to small businesses into aggregate fluctuations (Kiyotaki et al., 1997; Bernanke et al., 1994). The paper also provides insights into the nature of entrepreneurship and small businesses, following Hurst and Pugsley (2011) and has implications for entrepreneurial dynamics as documented by Birch (1979), Evans and Jovanovic (1989), Holtz-Eakin et al. (1993)), Hurst and Lusardi (2004) and Foster et al. (2013). This paper also gives insights into lending relationships, soft and hard information, and the use of IT in banking that have been studied historically by Petersen and Rajan (2002).

The paper proceeds as follows. In Section 2, I describe the new 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, and Section 6 concludes.

2 Data

Large-scale, high-frequency data on the financials of small businesses in the US is limited[4]. Financial measures for large listed companies in the US are readily available from Compustat for large firms at quarterly frequency, but for smaller businesses, sources are limited. The Longitudinal Business Database and County Business Patterns from the US Census Bureau measure entry, exit and employment for all US firms, but do not include financial information.[5] 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 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 bookkeeping, either in-house or through an accountant. For obtaining reliable data for the study, I restrict the sample to all companies who have subscribed beyond the trial period of the software, have recorded business addresses, and can be matched to Dun and Bradstreet, which I use to measure additional background characteristics. I exclude accounting firms (NAICS 5412), which sometimes handle multiple companies under one identifier, non-profits and firms in non-classifiable industries (NAICS 99).[6] The final sample consists of a panel of 141,678 firms for the period 2007-2013. Of

[4]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. 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 and Klenow (2009).

[5]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.The AMADEUS and FAME datasets cover accounting data well for private firms in the UK and Europe, but there are no such datasets for the US.

[6]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).

these, 77,124 firms link bank accounts into the software.

Transactions are imported from the firm's business bank account or an employee of the firm enters them on a regular basis.[7] The data allows capture of 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.[8] 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. Representativeness in firm size is important for the external validity of any results that distinguish between the borrowing behaviour of firms of different sizes. I compare data for 2010 (the middle year of my sample) 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.[9] Data Appendix Table B.1 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, 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 in both the population and the sample. Data Appendix Table B.3 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

[7]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.

[8]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.

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

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 B.4.

Summary statistics for the sample for 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.[10] 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.[11] 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.

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).[12] 530 insolvent banks were

[10] 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.

[11] 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.

[12] 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.

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.[13] 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 value of the owner's personal collateral, which matters 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 includes estimated 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.[14] 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 generate 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 (Aubuchon et al., 2010). Omitting these can result in an upward bias of the 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

[13]We may expect stronger effects of bank shutdown relative to acquisition of the failed bank by a healthy institution. However, by design, the FDIC attempts to auction off the insolvent bank and we do not have sufficient data to explore this heterogeneity.

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

on each county having many banks, 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. Finally, 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. 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 account 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.

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 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 $Log(Credit_{it}/Sales_{it})$. 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 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.

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. 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. 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 (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 small firms which faced bank failures between 2007-2013 were different from small firms which did not face bank failure, in 2006 on measures of credit and performance.[15] If the affected firms have lower credit and poorer performance when the bank was relatively healthy, selection may be driving the impact of credit on this set of firms rather than the impact of bank failures. 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 levels and logs for income, expenses and trade credit. I also compare the number of transactions, and size measured by employment or log employment. As shown in the table, there is no statistical difference between affected and unaffected firms on these credit, performance and size measures.

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 Panel B of Table 3, this is not the case: 2 years prior to bank failure we do not see significant differences in log credit.[16]

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. In Table A.2, the difference in credit one and a half years after bank failure is very weakly significant after controlling for demand shocks.

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

[16] The finding that there is no impact of small business credit prior to the event of failure supports the choice of failure as the appropriate bank credit supply shock. An alternative shock could be bank distress, but the placebo test and as a regression on quarter dummies around failure indicate that credit supply declines only after the event of bank failure. This is also visible in the matching exercise shown later in this section. This may be because small business lending is not a large entry on the bank's balance sheet, as described in section 4.2.4.

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 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.[17] Firms which have similar observable characteristics should have similar demands for credit and based on their characteristics have access to similar lenders. Figure 2 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.[18] 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 2. 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.

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

[18] 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.

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.3. 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.[19]

4.2.4 Reverse Causality

Another potential concern is reverse causality. Did the decline in firm credit demand push banks to failure? Evidence from the literature suggests otherwise. Although smaller banks are better at processing soft information used in lending relationships (Berger et al., 2005), small business loans contribute a small share to the assets on the balance sheet for all banks. Jayaratne and Wolken (1999) measure the share of small business loans to be 3% of the balance sheet for large banks and 9% for smaller banks. Banks were likely driven to failure due to exposure to the real estate market (Santos, 2011) or exposure to toxic assets (Erel et al., 2014). They also faced failure due to contagion effects through being linked to specific institutions (Ivashina and Scharfstein, 2010; Chodorow-Reich, 2014).

[19] More generally, the firms in the dataset have lower exit rates than those in the Census. This may be explained by firms in the sample being older and having large enough business volumes to be using accounting software.

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 and 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 2 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.[20] 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 and 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.

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

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.

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 is also not sensitive to the cutoff of 10 employees for distinguishing between micro and small firms. These results, combined with the previous results on bank failures suggest 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 and 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.[21] 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 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.

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

6 Additional results

In this section, I include additional results for 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.

Micro firms may enter into banking relationships for reasons which also 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.4 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 (Duygan-Bump et al., 2010). To study this, I follow the literature and use the measure of external dependence on finance developed by Rajan and 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.[22]

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 and Zingales (1998) for both credit shocks.[23] The results are shown in Appendix Table A.5. 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.

7 Conclusion

The lack of firm-level financial data for small businesses restricts the study of credit shocks during the Great Recession to looking at real outcomes for small businesses or focusing on the financial outcomes for large firms. Given the high share of small businesses in the

[22] Cetorelli and 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.

[23] 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.

firm population, the contribution these firms have for employment and the severe credit constraints such firms might face, these small businesses may drive aggregate fluctuations in the economy and it is thus importatant to understand the credit outcomes of such firms.

In this paper, I use a new dataset on small business financials to study small business financing during the Great Recession in the US. I show credit supply shocks in the banking sector and the real estate market during this period drive declines in 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 linked to the firm. The response of firm credit to bank failure is temporary, and is higher when the firm has fewer banking relationships and also increases 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.

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. These results are important from a policy perspective. Given that these firms may affect employment and investment differently, these affect the directions policy must take to alleviate shocks from either of these two channels.

The paper raises questions for further research. Advancements in IT use in the banking sector codify soft information, and more information is transferrable across lenders (Petersen, 2004; Petersen and Rajan, 2002). Understanding the role of IT in the transfer of information during the closure and restructuring process of the Federal Deposit Insurance Corporation can help determine how to reduce the loss in credit to small businesses that occurs during the resolution process.

The channel of trade credit is also important for small businesses (Petersen and Rajan, 1997; Blasio, 2005; Biais and Gollier, 1997). An interesting dimension would be to examine the role of trade credit in buffering shocks to formal credit. As trade credit is taken from suppliers and given to customers, the challenge here will be to separate the demand and credit supply channels for a firm.

The incorporation of micro-level effects into macro frameworks has been addressed by Gertler and Gilchrist (2018), however the Great Recession has led to integration of micro channels into macro models in greater detail, a promising direction towards further understanding the role of small businesses in driving aggregates.

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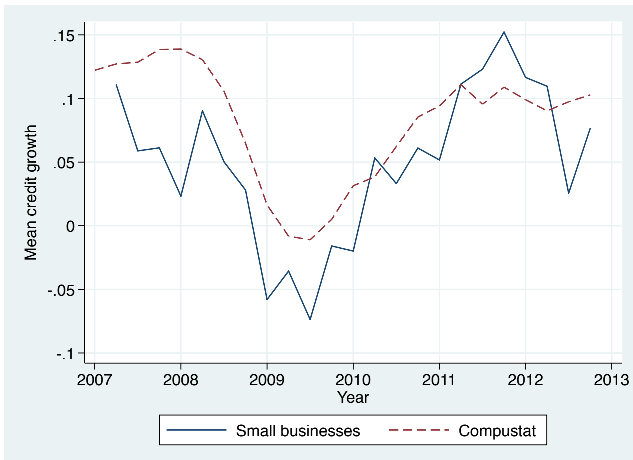
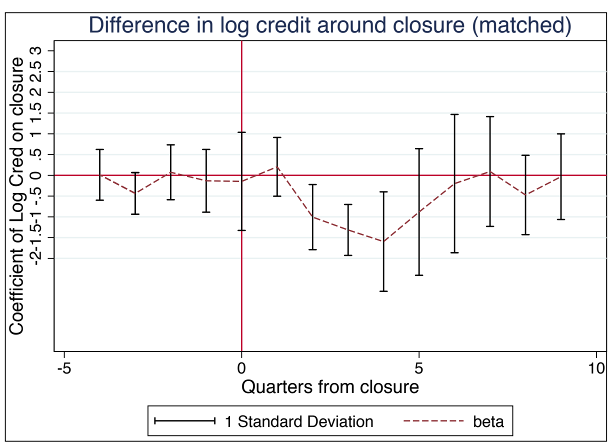
Figures and Tables

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 winsorized at the 1% level.

Figure 2: 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.

Table 1: Summary Statistics

	Mean	Std.Dev	Min	Max	Median
All firms					
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	6,299,158,930	0
Credit ($) >0	335,579	16,083,934	40	6,299,158,930	39,544
Micro firms					
Size (employees)	2.72	2.54	0	9	2
Revenue ($)	872,260	55,399,336	0	7,040,920	228,486
Credit ($)	55,375	8,097,182	0	6,299,158,930	0
Credit ($) >0	347,510	20,281,938	43	6,299,158,930	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	237,090,994	0
Credit ($) >0	315,857	2,516,734	35	237,090,994	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 winsorized 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 winsorized 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	90,469.66	74,773.31	0.479	0.290
Log(Credit)	10.69	10.60	0.779	0.888
Log(Credit/Sales)	-2.69	-3.13	0.143	0.291
Income	1,068,263	1,326,934	0.112	0.163
Log(Income)	13.40	13.53	0.319	0.196
Expenses	728378.9	885777.8	0.2663	0.277
Log(Expenses)	12.89	13.09	0.138	0.021
Trade credit	186674.5	330608	0.1628	0.104
Log(Trade credit)	11.35	11.75	0.145	0.100
Number of Transactions	7712.27	8215.73	0.623	0.922
Employment	34.09	30.12	0.2476	0.603
Log Employment	3.21	3.11	0.1612	0.367

(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

Notes. Panel (A) shows balancing tests for small 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. 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 winsorized 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 winsorized 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 winsorized 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.

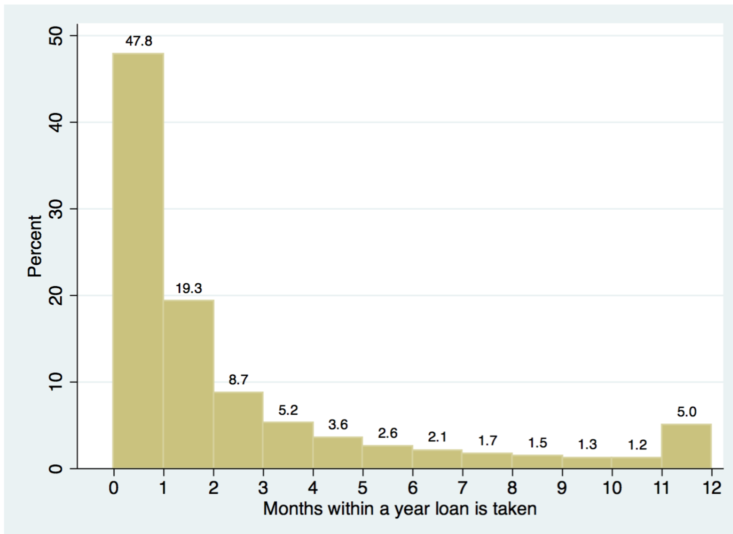
Table 6: Tradability and House Prices

	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 and 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.

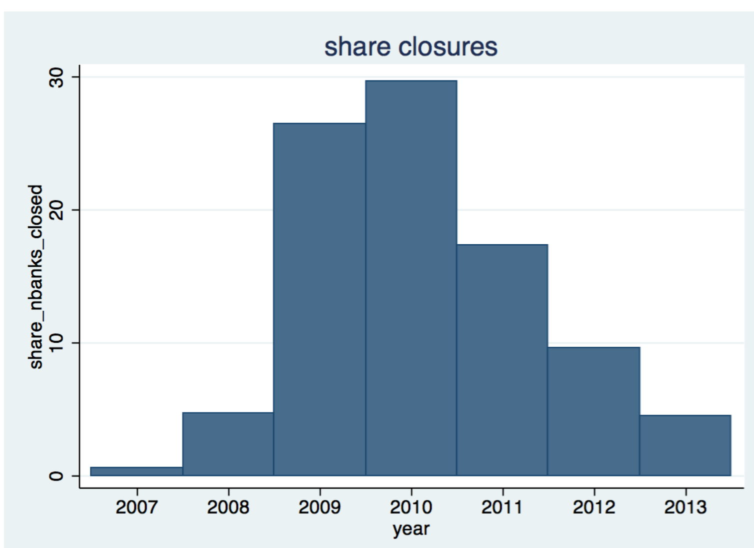
A Additional Figures and Tables

Figure A.1: Frequency of Borrowing



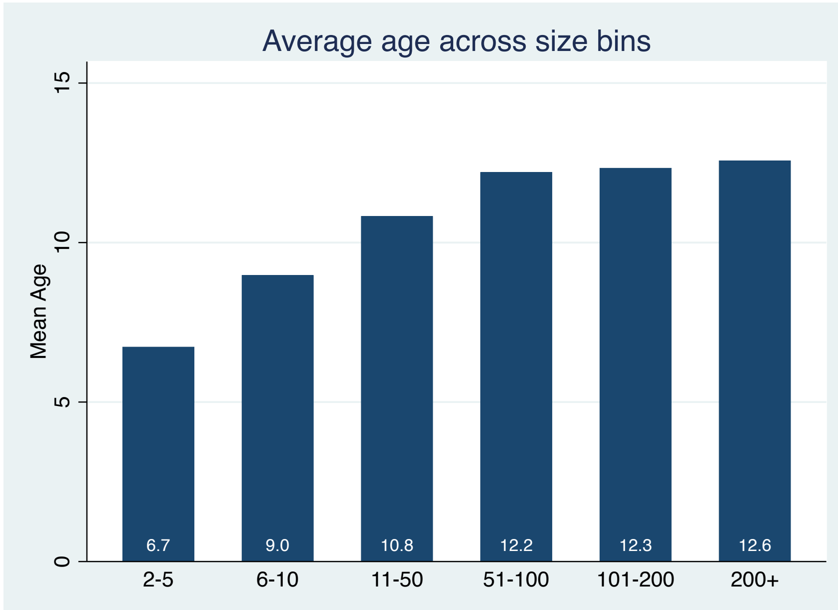
Notes. Number of months in a year that firms borrow. The sample is for 141,678 firms restricted to those with at least one year of borrowing in the dataset.

Figure A.2: Bank Failures During 2007-2013



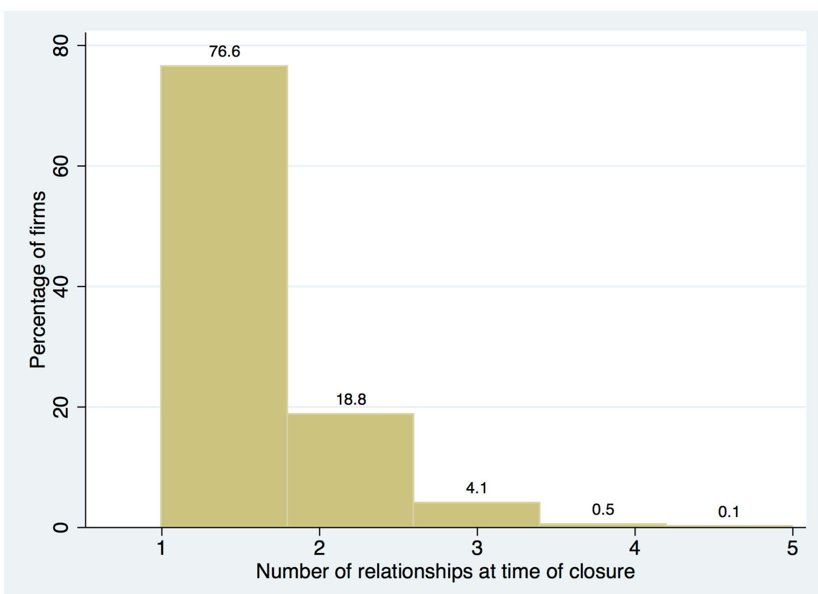
Notes. Bank failures during 2007-2013. Source: Federal Deposit Insurance Corporation.

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 winsorized at the top and bottom 1%. Regressions are weighted by employment. All standard errors are clustered at the firm level.

Table A.2: 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.. Placebo test for the response of firm credit to bank closure measured six quarters before 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 winsorized at the top and bottom 1%. All regressions are weighted by the number of employees. Standard errors are clustered at the firm level.

Table A.4: 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
Unclassified	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.3: 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.5: 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 and 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 A is all 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.

B Data Appendix

B.1 Representativeness

Table B.1: 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 B.2: 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 B.3: 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 B.4: 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.