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Abstract

Small businesses can overcome asymmetric information in credit markets using collateral and by forming lending relationships. Differences in whether a small business is predominantly "collateral-dependent" or "relationship-dependent" can lead to a differential impact of different types of credit shocks during recessions. I use novel transaction-level data from a leading online accounting software in the US for a large and representative sample of small businesses, for whom I measure two types of shocks at the firm level: bank insolvencies, and changes in real estate prices at the business owner's residential location. I find that bank insolvencies lead to a substantial decline in firm credit, however the effect is driven by the effects on relationship-dependent firms. In contrast, house price movements significantly affect the credit of collateral-dependent firms as expected, but do not affect the credit of firms that are predominantly dependent on relationships. The analysis thus reveals that credit shocks with different origins can have differential impact within the small business universe, due to heterogeneity in firms' sources of borrowing.

JEL Classification: N/A

Keywords: great recession, small businesses, Credit shocks

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Small businesses can overcome asymmetric information in credit markets using collateral and by forming lending relationships. Differences in whether a small business is predominantly "collateral-dependent" or "relationship-dependent" can lead to a differential impact of different types of credit shocks during recessions. I use novel transaction-level data from a leading online accounting software in the US for a large and representative sample of small businesses, for whom I measure two types of shocks at the firm level: bank insolvencies, and changes in real estate prices at the business owner's residential location. I find that bank insolvencies lead to a substantial decline in firm credit, however the effect is driven by the effects on relationship-dependent firms. In contrast, house price movements significantly affect the credit of collateral-dependent firms as expected, but do not affect the credit of firms that are predominantly dependent on relationships. The analysis thus reveals that credit shocks with different origins can have differential impact within the small business universe, due to heterogeneity in firms' sources of borrowing.

JEL CODES: G210, R310, D220
KEYWORDS: Great Recession, Small businesses, Credit shocks

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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 et al., 1996). Financially constrained small businesses are more sensitive to economic shocks and given their importance in the economy, drive aggregate dynamics (Bernanke, 1983). The literature documents two ways in which small businesses overcome asymmetric information. First, by circumventing dependence on information through leveraging collateral. For small businesses, this often means the use of personal housing as collateral. Second, firms can enter into lending relationships and borrow on the basis of shared information.[1]

Depending on how a small business has solved the problem of asymmetric information, the nature of the credit shock will determine which firms get affected. Specifically, firms which have leveraged personal housing collateral to overcome asymmetric information will be able to borrow more with increases in real estate prices. In contrast, firms which have established relationships with loan officers at banks may face credit constraints in the case of bank failure, when information about the firm is lost.

With the slow recovery in the US following the Global Financial Crisis, there has emerged a large body of literature on the role of shocks to collateral values for firms' investment and employment decisions.(Chaney et al., 2012; Chodorow-Reich, 2014; Nguyen, 2014; Adelino et al., 2015; Duygan-Bump et al., 2015; Greenstone et al., 2020).[2] However, the literature incorporates heterogeneity in the sources of borrowing among small businesses only to a limited extent. The distinction between how firms borrow will have important consequences both theoretically, for refinements of models with financial sector shock propagation, as well as for economic policies targeted at small businesses.

To study the sensitivity of these two types of firms to credit shocks, I use novel transaction-level data from a small business accounting software in the United States. Along with firm financials at high-frequency for a large and representative sample of small businesses, the data allows me to observe the business owner's residential address, as well as the bank with which the firm holds their business bank account. Using these, I will estimate the impact of two distinct shocks on credit outcomes at the firm-level.

The first shock is failure of the firm's bank, designed to capture disruptions in lending relationships. Firms depend on sharing information with banks through relationship lending. A bank failure destroys these long-standing credit relationships and leads to a loss of firm-specific information, and firms have to rebuild relationships with either the acquiring institution or new lenders. To estimate the impact of bank insolvencies on firms, I match the banks of firms in my baseline sample to the set of banks which became insolvent and underwent the Federal Deposit Insurance Corporation (FDIC) resolution process. An FDIC-assisted

[1] For example, Evans and Leighton (1990); Hurst and Lusardi (2004) document the role of personal wealth and assets in entrepreneurship, while Petersen and Rajan (1994); Berger and Udell (1995); Cole (1998); Uzzi and Lancaster (2003); Drexler and Schoar (2014) describe the role of lending relationships.

[2] See also, among others, Barone et al. (2018); Manaresi and Pierri (2019); Degryse and Van Cayseele (2000).

bank shutdown is both extremely short and unpredictable by design: the FDIC performs takeover operations in secret, with closed banks re-opening the next business day under new ownership of the acquiring institution. Loan officers from the insolvent bank are disbursed. This offers is an ideal opportunity for studying disruptions in lending relationships in the Great Recession.

The second shock I examine is house price movements at the owner's home location, capturing changes in the entrepreneur's ability to leverage collateral. A house price appreciation allows start-ups to extract additional home equity value from existing property and invest it into their business. My strategy follows the existing literature (Adelino et al., 2015; Ersahin and Irani, 2020). For studying the collateral lending channel, I take a firm-level measure of the shocks to values of the personal collateral of the owner. I begin with the home address of the business owner. I match the business owner's home address to the Zillow Home Value Index at the ZIP code level to examine how credit moves with house prices at the zip code level. The ability to measure both credit shocks at the firm level for a wide range of small businesses makes my dataset ideal for studying the impact of the two different channels on small businesses.

A critical challenge in measuring the role of credit supply shocks during a recession is controlling for contemporaneous declines in consumer demand during this period. Local demand shocks would affect credit outcomes through a firm's demand for credit rather than the supply. Omitting credit demand can result in an upward bias on estimates of the effect of supply-side credit shocks. To control for consumer demand, I build a firm-level time-varying demand index using movements in house price at the firm's customers locations. Second, I use fixed effects at the county-quarter level based on the firm's location. Third, I follow the literature and focus on firms in tradable industries, where demand shocks are delocalized.

Which firms depend on collateral and which ones depend on lending relationships? Firms may not have equal access to uncollateralized loans due to higher costs of information verification. Survey data suggests firms can be sorted by size. Data from the National Survey of Small Business Finances (2003) shows that for firms with less than 10 employees, 27% of collateralized lines of credit is through mortgages while firms with more than 10 employees have a share of 13%. In contrast, businesses with more than 10 employees have 29% of credit based on business valuations while those with less than 10 have only 9%.[3] Accordingly, I classify firms based on employment, with collateral-dependent firms being the firms with less than 10 employees and relationship-dependent firms those with more than 10 employees. This categorization is consistent with related work examining the impact of collateral shocks on firm-level outcomes. For example, Adelino et al. (2015) study the change in employment due to collateral price movements in the Great Recession and find firms with less than 10 employees as the group with highest sensitivity. [4] At the upper end, I restrict the sample to firms with less than 250 employees, consistent with the literature on firms sensitive to banking sector shocks (Chodorow-Reich, 2014).

[3]For more details, see Figure A.1 of the Online Appendix.

[4]In recent work, Lastrapes et al. (2020) find that firms with fewer than ten employees have stronger responses to a constitutional amendment expanding the scope of home equity loans in Texas.

To examine the role of FDIC-assisted bank failures, I begin with a matching and event study framework. I examine credit dynamics before and after the event of bank failure for bank shutdowns in the Great Recession. I pair every firm that faced bank failure to a firm with similar characteristics and local economic conditions whose bank did not fail. This controls for local economic conditions and demand-side shocks. I then measure the difference in credit outcomes between the two firms in each pair following bank failure. From the matching and event study exercise, I find that on average, relationship-dependent firms whose banks fail face significant credit declines relative to similar firms. After a period of six quarters, credit of affected firms recover to comparable levels.

To examine this further, I use a regression framework and find an overall average decline in credit following bank failure. However, the effects are driven by the subset of relationship-dependent firms. For these firms, there is an average of 25% decline in credit supply associated with bank failure. The corresponding coefficients for collateral-dependent firms are not statistically significant, and are much smaller in magnitude. This result is robust to a variety of specifications. These include using quarterly and annual measures of the level of credit, scaling the level of credit by sales, and using credit growth as an alternative outcome variable.

Firms which are less credit-worthy could be selectively associated with banks that have poorer performance and subsequently a higher likelihood of failure. I examine whether my results are confounded by selection effects. First, I confirm that firms which faced bank failures between 2007-2013 are not significantly different from firms which did not face bank failure based on measures of credit and performance in 2006, prior to all failures in my sample. Second, I perform a placebo test measuring 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 indicator for bank failure back by one and a half years and examine the impact on credit. Prior to bank failure, there is no significant difference in credit. This suggests selection is not driving the result.

Next, I study the collateral-lending channel using the Zillow Home Value Index, capturing the median house value at the business owner's home address. Here, I find house price movements affect the credit of collateral dependent firms more substantially than the credit for relationship-dependent firms, as we might anticipate. Since I am able to observe firm credit, I can determine the magnitude of the effect: for collateral-dependent firms, a 1% change in the house price index at the owner's zip code is associated with a 0.3% change in long-term credit at the firm-level. The corresponding coefficients for relationship-dependent firms are both smaller and non-significant. The results are confirmed in robustness tests, where I focus on tradable sectors. The magnitude remains stable and significant along the spectrum of tradability, supporting the role of credit supply.

I further establish that the sample of firms which link data from bank accounts and those which do not are not different on observables. Finally, I find the results to be stable to estimating the impact of both shocks simultaneously: I again confirm that collateral-dependent small businesses are sensitive to house price movements while relationship-dependent ones show significant declines in credit following bank failure.

My paper contributes to the literature on the impact of bank insolvencies on firms. Benmelech et al. (2019) find disruptions in credit supply for large industrial firms due to bank failures in the Great Depression. Ashcraft (2005) finds that FDIC-induced failures of healthy banks cause declines in local economic activity. Similarly, Nguyen (2014) finds that bank branch closings lead to declines in local employment. I extent the literature by studying the impact of bank failures in the Great Recession, distinguishing between different firms within small businesses.[5] Furthermore, in the absence of detailed data on small businesses, the literature has either quantified effects at the firm on large firms or using aggregate real outcomes for small firms. I quantify the financial impact of bank failure on the credit for small businesses at the firm-level, finding a decline of 25% in the new long-term liabilities following bank failure for relationship-dependent firms.

This paper also contributes to the literature on the role of the collateral-lending channel in the Great Recession, by estimating the impact on credit at the firm level for small businesses. Adelino et al. (2015), the first to study this channel, find large real effects of house price changes on local employment. Ersahin and Irani (2020) find sizable investment effects for large private firms, while the magnitude of the effect for public firms found by (Chaney et al., 2012) are smaller. I find the credit response of firms to be 0.3% for every 1% change in collateral prices, in line with previous estimates by Kleiner (2014) using data from the UK, which finds estimate firms extract $0.25 of debt for every $1 increase in real estate value.

The paper provides underlying micro-level evidence that informs the literature on dynamic models with financial frictions, beginning with Bernanke et al. (1999) and Kiyotaki and Moore (1997). Some models allow for heterogeneity across agents, for example Punzi and Rabitsch (2015) model investors' with differential ability to borrow from collateral. However, most models assume representative financially-constrained agents. Expanding this literature to incorporate different sources of borrowing for small businesses is an exciting avenue for research.

Finally, the paper also provides insights into the role of hard versus soft information in banking. My results suggest that information about borrowers was lost during the bank resolution process in the Great Recession, despite the advancements in IT in the banking sector in recent decades (Petersen and Rajan, 2002). My results support substitution between collateral and information in lending markets, consistent with (Manove et al., 2001).

The paper proceeds as follows. In Section 2, I describe the new dataset. In Section 3 I examine the response of firm credit to bank failures. In Section 4, I study the role of house price movements on small business credit. Section 6 concludes.

[5] My findings are in line with Chodorow-Reich (2014) and Greenstone et al. (2020), and more broadly (Khwaja and Mian, 2008) and Santos (2011).

2 Data

2.1 Accounting data

I use data from an online accounting software provider which contains financial transactions for more than 4 million companies globally. Firms use the software for in-house book-keeping. They directly import transactions from business bank accounts, or they can manually enter transactions with timestamps into the software. Then, firms categorize transactions under categories provided by the software, for example as "accounts tradable", "income", etc. The software uses this information to construct up-to-date financial statements at the front end. I use the back-end data of time-stamped transactions with firm IDs to construct a panel.

I define my sample of firms for the panel as all companies from the software with registered addresses in the US which have had a paid subscription to the software. I further restrict to firms for whom I can find a match in the Dun and Bradstreet database. Details of the sample construction are described in Section A.3 Online Appendix. The filters yield a final sample 141,678 firms. The sample is representative of the US population across firm size, as described in Table A5. This is important for the external validity of the results, which hinge upon the representativeness of firms of different sizes in the sample relative to the population, used to define collateral-dependent and relationship-dependent firms. In addition, in Table A6 and A7, I show the sample is representative across industries. This is especially relevant because in my robustness tests, I will use the industry classification to control for demand shocks following the classification of industries into tradable sectors following Mian and Sufi (2014).

The primary outcome variable I use in my analysis is credit, defined as the sum of all transactions categorized by the firm as long-term liabilities, and where the transfer is *from* a lender *to* the firm.[6] While the original disaggregated transactions-level data has the timestamp of each credit transaction, small businesses borrow long-term at most a few times in the year. This is consistent with literature on firm investment, which documents that patterns of adjustment of long-term capital are lumpy (Bloom et al., 2007). For this reason, I aggregate long-term credit to the quarterly level, and match all other variables in my analysis to this frequency when constructing the panel.

Throughout the paper, I use employment to distinguish between collateral-dependent and relationship-dependent. To measure employment, I extract information from the payroll feature of the software. Firms can add and remove employees into the payroll register, and the software tracks the dates for these changes. I cumulate the number of employees present on the payroll of the firm between the start and end of each month to construct a time-varying measure of employment.[7] I exclude the self-employed and firms with more than 250 employees. Finally, I define collateral-dependent as those with 2 to 10 employees and relationship-dependent firms as those with 11 to 250 employees.

[6]The focus on new loans allows me to capture the effects of new lending relationships, see for example Schivardi et al. (2017).

[7]I aggregate this to the quarterly level by averaging across quarters in the month to match the frequency of the credit measure.

Table 1: Summary statistics

Variable:	Mean	Std. deviation	5^{th} percentile	Median	95^{th} percentile
Panel A: Full sample					
Employees	15.51	25.06	2	7	60
Age (years)	9.03	11.20	0	5	31
Sales (USD)	877,930.00	1,353,048.00	11,596.84	399,872.90	3,495,136.00
Credit (USD)	128,764.50	253,015.80	365.61	34,689.57	612,246.90
Credit/Sales	0.2153	0.4595	0.0008	0.0655	0.9067
Credit Growth	0.16	1.47	-2	0.18	2
Transactions	5,849.30	11,236.30	62	3,277	19,307
Panel B: Collateral-dependent firms					
Employees	4.37	2.20	2	4	9
Age (years)	7.77	10.37	0	4	28
Sales (USD)	663,858.40	1,121,275.00	7,583.40	290,661.80	2,624,314.00
Credit (USD)	107,014.00	224,582.20	300.00	28,296.00	498269.80
Panel B: Relationship-dependent firms					
Employees	32.54	33.17	10	20	101
Age (years)	12.39	12.55	2	9	36
Sales (USD)	1,433,384.00	1,700,393.00	76,777.78	833,849.90	5,066,329.00
Credit (USD)	170,712.70	295,864.60	554.97	51,758.12	802,035.20

Notes. Summary statistics for baseline sample. The sample consists of 844,882 firm-year observations for 141,678 individual firms between 2007 and 2013. Annual employment is the March monthly value from the payroll register, bounded between between 2 and 250 employees. Age is the minimum between the year of incorporation available in Dun and Bradstreet and the year of the first transaction in the software. Credit is the sum of all new long term liabilities issued to the firm in the given year. Credit and income are censored at the top 1% level.

Summary statistics for the variables are shown in Table 1. In Panel A, I show summary statistics for the full sample. Firms in the dataset are small: the mean firm has 15.5 employees and median firm size is 7 employees. The 95^{th} percentile is 60 employees, consistent with the distribution of firm size in the US population. The average firm in the sample is 9 years old, and the overall age distribution in the sample has a slightly higher share of older firms relative to the US population. The mean annual sales of firms during the sample period is 877,930 dollars, and median is approximately 399,872 dollars. The average and median annual credit of firms in the sample is 128,764 dollars and 34,689 dollars respectively. I also tabulate two more variables used in the analysis: credit scaled by firm sales, on average this ratio is 0.2, and sales growth calculated following Davis et al. (1998) as $2 \times (Credit_t - Credit_{t-1})/(Credit_t + Credit_{t-1})$, which take mean and median values of 0.16 and 0.18 respectively. Firms in the sample have on average 5849 transactions a year.

In Panel B and Panel C I split the sample into collateral-dependent and relationship-dependent firms as described above and tabulate key variables across the two groups. Collateral-dependent firms are smaller than relationship-dependent firms based on employment (by definition). They have on average 4.4 employees (median is 4). In contrast, relationship-dependent firms have on average 32.54 employees (median is 20). These are younger than relationship-dependent firms (mean age 7.77 years for collateral-dependent versus 12.4 for relationship-dependent). The mean annual sales in the first group is 663,858 dollars (median is 290,661 dollars), while for the second group, average sales a year is 1,433,384 dollars (median is 833,849 dollars). Interestingly, collateral-dependent firms have lower annual credit than relationship-dependent firms: on average annual credit of 107,014 dollars, in contrast to 170,712 dollars.

2.2 Bank failures

I link bank failures to this panel using FDIC data. For the firms which directly import transactions from their business bank account, I observe the name of the bank where the account is hosted. I match the names of these banks to the FDIC's failed bank list of deposit insured banks that were shut down with government assistance during the period of 2007-2013.[8] Out of the 530 institutions in the FDIC "failed bank list", 130 matched to the list of banks in the software. I assign the date of bank failure from the FDIC failed list to the firm, and use this to construct a time-varying shock at the firm level.[9]

2.3 House price shocks

I augment the firm panel with house prices at the owner's home location. First, for all firms in my baseline sample, I retrieve the the ZIP code of the owner's home address from background details on the business stored by the software. With this as the identifier, I link the dataset with the Zillow Home Value Index (ZHVI). The ZHVI is comparable to other house price indices (Guerrieri et al., 2013), but has the advantage of measuring house prices at the ZIP code level. The index constructed using all types of homes (single, condominium and cooperative), including estimated prices for homes that are not for sale.[10]

2.4 Demand measures

The software also contains additional information which enables me to control for contemporaneous demands shocks in my analysis. The address book feature of the software records addresses of each firm's customers. I calculate the distribution of customers across zipcodes for each firm, and combine this with house price data from the ZHVI at the customers' location. I thus construct a measure of demand at the firm-level. I describe details of the firm-level demand index construction in the next section.

Finally, I source additional background variables which I use in the other strategies to control for demand. For this, I match firms in my sample to the Dun and Bradstreet database. From here, I obtain the address of the business, which I match to the list of US Counties. In addition, I also obtain the standard NAICS industry classification of each firm. I use this to classify firms into tradable sectors, following Mian and Sufi (2014)

[8] The list of failed banks from the FDIC is available here.

[9] Small businesses in the software have very few lending relationships, consistent with information-sharing incentives documented in the literature (Petersen and Rajan, 1994). For the few firms which experience more than one bank failure, I only use the first.

[10] In order to match the ZHVI to the panel, I aggregate the original monthly index to the quarterly level by averaging across the months in each quarter.

3 Bank Failures and Firm Credit

Lending relationships allow small, non-transparent firms to share information with banks, and can play an important role in enabling access to credit (Petersen and Rajan, 1994). Firms may face tighter credit constraints when banks fail, as the process of bank restructuring and changes in management involves the transfer of loan officers, and information about the firm is lost. On the other hand, firms which borrow on the basis of collateral may be less affected, as these firms can pledge their collateral to a new lender.

3.1 Preliminary analysis

I begin with analyzing the impact of a bank failure on small businesses credit by implementing an event study combined with propensity score matching.[11] An event study helps us visualize the trajectory of changes in credit of an affected firm around the event of the bank failure. This includes the timing and magnitude of the impact, as well as the path of recovery. However, as I am estimating an outcome of a bank failure in the midst of a recession, I cannot directly apply the event study methodology to the problem: contemporaneous local economic factors in the economy during the recession may also lead to declines in credit, confounding my results. This would lead to an overestimation of the impact of a bank failure on credit. To control for such effects, I match firms affected by bank failure to firms within the same area, industry, and also with similar characteristics. These are likely to face the same local economic shocks but do not experience bank failure. I match using propensity score to ensure that the control firms had similar likelihood of being linked to a bank that fails, and are thus appropriate controls for affected firms. Thus, in this proposed strategy, bank failure is both the event, as well as the treatment.

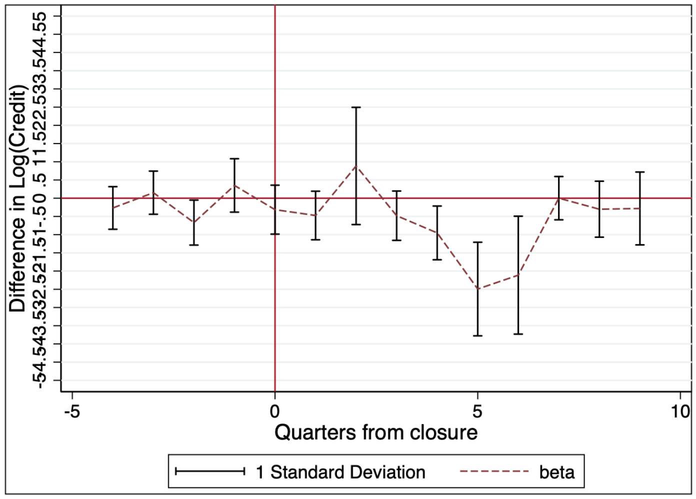
For my estimation, I take as treatment bank failures during 2008 and 2009, and focus on relationship-dependent firms. For each of these firms, I identify an appropriate control from the pool of firms which did not experience bank failure. I match on both categorical as well as continuous variables. First, I start with exact matching on the categorical variables: the state and industry of the treated firm. Potential controls for each treated firm are thus the pool of all firms within the same 2 digit NAICS industry and the same state as the treated firm. Within the pool of exact matches on industry and location for each firms, I further identify one "control" firm for each "treated" firm that faced bank failure using propensity score matching on continuous firm characteristics.[12] The control firm thus selected is similar to the treated firm in the propensity to be paired to the bank that failed. In addition, the control firm faces the same demand effects. With this, I account for variations in demand by firm characteristics, even within location shocks which vary at the industry-geography level (Acharya et al., 2019; Degryse et al., 2019).

With the matching procedure in place, I now have pairs of firms where one firm faces bank

[11] This empirical strategy combines the event study methodology originally by Fama et al. (1969) and the propensity score matching approach of Rosenbaum and Rubin (1983). Other contexts where these methods have been combined include Nanda and Ross (2012) and Sugeng et al. (2016).

[12] I use propensity score matching with Mahalanobis distance on the log of age, and credit in the year prior to failure with caliper 0.01 and one nearest neighbor per affected firm.

Figure 1: Bank failure and firm credit: matching and event study



Notes. Matching and event study of firm credit around bank failure. The y-axis of the graph shows the difference between $Log(Credit)$ of relationship-dependent firms in the data whose banks failed versus matched firms whose banks did not fail, where credit is the sum of new long term liabilities to the firm in a quarter. The x-axis shows time in quarters from closure, where the vertical red line at 0 marks the event of closure of the failed bank of the treated firm of the pair. Firms were matched using propensity score based on 2 digit NAICS, state, log(age) and log(credit) in the year before closure, with one match per affected firm and caliper for propensity score 0.01. The graph also marks confidence intervals of 1 standard deviation, created using 500 bootstrap replications from the sample.

failure while the other firm has similar access to the failed bank and faces similar demand shocks as the affected firm. I now assign an event timeline to each pair, with 0 marking the quarter in which the treated firm experienced bank failure. Under this setup, I calculate the difference in credit for the treated versus control firm for the quarters prior to, during, and after the event of bank failure. Credit is measured as the sum of long term liabilities to the firm in a given quarter, following Section 2.

Figure 1 shows the results from performing the event study for the matched pairs of firms. The average difference in $Log(Credit)$ for treated and control firms is shown for 4 quarters before, to 10 quarters including and after the event of bank failure. Standard errors are bootstrapped following Caliendo and Kopeinig (2008), and show one standard deviation around the mean difference in credit across pairs. As we can see from the graph, following a bank failure, affected firms initially show a relative decline in credit, and then a recovery to comparable levels of credit to that of control firms. Overall, the average difference in credit lasts for up to 6 quarters, after which it is no longer significant. This suggests asymmetric information as the channel driving the impact of bank failure on firm credit, consistent with the idea that information contained in the lending relationship is lost when banks fail, and it takes time to establish relationships with new lenders.

3.2 Empirical strategy

Next, I estimate the impact of bank failures on firm credit using a regression framework. The regression of a credit measure on an indicator for bank failure would ideally capture the impact of disruptions in lending relationships to the firm's long term credit through credit *supply* shocks. However, this coefficient may be upwardly biased if one omits to control for contemporaneous declines in firm credit demand, arising, for example, from consumer demand declines, originating from local economic shocks.

To control for consumer demand, I build a firm-level, time-varying demand index using each firm's customer addresses. I use house prices at the location of each firm's customers, weighted by the share of the firm's customers across locations. The demand index thus constructed varies at the firm-quarter level. The identification strategy relies on the large consumption responses to local house price movements found in the literature (Mian et al., 2013; Campbell and Cocco, 2007). In the context of my analysis, changes in house prices for customers of a firm lead to shifts in demand for the firm's products. This consequently leads to changes in the firm's demand for credit. With this measure, I leverage the heterogeneity in local-level house prices across the US (Ferreira and Gyourko, 2012). In this setup, each firm will face a different sequence of demand shocks, depending on how the firm's customers are distributed geographically.

Formally, I construct the index as follows. I leverage the data on customer locations available in the software's address book feature. For each firm, I first define the market area of the firm as all the zip codes in which the firm records customers. Then, for each zip code in a given firm's market area, I calculate a relative weight to assign to the zip code. This is the share of the firm's customers in the zip code with respect to the firm's total number of customers. Note that these weights vary across firms. Then, for each firm, I combine the relative weights with the zip code level house price series from Zillow. Since each firm has different weights over the set of all zip codes, the final series will vary over firms as well as over time. I can write the demand index Dem_{it} as:

$$Dem_{it} = \sum ZHVI_{it} * w_{iz} \tag{1}$$

where the weights w_{iz} are the share of total customers a firm records in a given zip code, and $ZHVI_{it}$ is the median house price in the zip code in quarter t.

With the firm-level demand index in place, I estimate the following equation:

$$Log(Credit_{it}) = \beta Fail_{it} + Dem_{it} + f_i + e_{it} \tag{2}$$

where the outcome variable $Log(Credit_{it})$ 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 equals one if firm i has experienced a bank failure in the previous 6 quarters, based on the trajectory of credit seen previously in the matching and event study. To control for demand, I use the demand index Dem_{it} described above. The regressions also include firm fixed effects f_i, to account for unobservables at the firm-level. Standard errors are clustered at the firm-level, to account for residual correlation across observations within a firm across time.

As an alternative strategy, I also control for demand using Quarter×County fixed effects to control for demand while studying credit supply. The identification strategy assumes that credit shock occurs at the firm level and varies across firms, while local demand shocks are similar for firms in the same county in a given quarter (Acharya et al., 2019; Degryse et al., 2019).

Finally, I also follow the literature and control for demand by restricting my sample to tradable sectors.[13] As customers in tradable industries are more dispersed, this limits the bias introduced by contemporaneous local demand shocks. To implement this strategy, I follow the categorization of industries to tradable sectors by Mian and Sufi (2014), where a 4 digit NAICS industry as tradable either if the sum of its imports and exports is higher than \$10,000 per employee, or if the total sum exceeds \$500 million. Retail industries, restaurants and grocery are classified as non-tradable.[14] If the results do not hold within tradable industries, then the relationship between bank failures and firm credit is understood to be driven largely through demand. Else, we can infer that the disruptions in credit originated from bank failures.

3.3 Results

Table 2 shows the results from estimating the specifications described above. Throughout the regressions, I control for firm characteristics using firm fixed effects and cluster standard errors at the firm level. In Panel A, I estimate the impact of bank failure controlling for demand using the firm-level index. I begin in Columns (1)-(3) with estimating equation 2. Column (1) shows the specification for the full sample. The coefficient β takes value -0.275. This implies bank failure leads to a 24% decline in bank credit, significant at the 1% level. However, when the sample is split into firms predominantly dependent on collateral and firms predominantly dependent on relationships, it is evident that the effect is driven by the second group: in Column (2), the same specification is estimated on the subsample of collateral-dependent firms only, and the estimated coefficient is smaller in magnitude at -0.096, and no longer significant. In contrast, in Column (3) the regression is restricted to the subsample of relationship-dependent firms. The coefficient is now both larger at -0.291 as well as significant at the 5% level. The coefficient value of -0.291 corresponds to a 25% decline in the average long-term credit of relationship-dependent firms, for six quarters following bank failure.

In Columns (4)-(6), I control for demand shocks using quarter-county fixed effects. The results are similar to the results in Columns (1)-(3). In Column (4), for firms of all sizes, there is a significant effect of bank failure on firm credit, with a coefficient of -0.295 significant at the 1% level. This corresponds to 25.5% decline in firm credit following a bank failure. In Column (5), the same regression specification for collateral-dependent firms yields a coefficient which is both smaller in magnitude at -0.035 and no longer significant. In Column (6), where the

[13] See for example Adelino et al. (2015).

[14] See the online appendix of Mian and Sufi (2014) for the full list of tradable and non-tradable industries.

sample is restricted to relationship-dependent firms, the effect is significant at the 1% level with a coefficient of -0.362 (corresponding to 30.4% decrease in credit associated with bank failure).

To further validate the results, in Columns (7)-(9) I restrict the sample of relationship-dependent firms to tradable sectors. For this set, I begin with the benchmark regression, using firms in the industries for which a tradability measure is available.[15]. The coefficient on bank failure takes the value of -0.234, similar to the corresponding coefficients in Columns (3) and (6). In Column (8), I exclude industries in the construction sector. The coefficient remains similar at -0.264 and significant at the 5% level. In Column (9), I exclude firms in construction as well as non-tradable industries. The coefficient on bank failure remains similar in magnitude at -0.266, significant at the 5% level. The results using tradable sectors are similar to those in Columns (1)-(6), further alleviating any concerns that impact on firms is driven by demand shocks.[16]

In Panel B of Table 2, I check if the results are robust to the frequency of estimation, by aggregating the data to the annual level.[17] In this case, I measure bank failure as an indicator that takes value 1 for the year of failure and the subsequent year. The results are shown in Columns (1)-(3). The estimated coefficient at the annual level is slightly larger at -0.563, corresponding to an average decline of 43% in credit. In line with the quarterly results, the coefficient is even higher for relationship-dependent firms at -0.716 (a decline of 51.1%), significant at the 5% level. As before, the coefficient for collateral-dependent firms remains smaller in magnitude as well as insignificant.

I also confirm the results are robust to the outcome variable. In Columns (4)-(5) of Panel B, I take the the outcome variable as credit growth. Following Davis et al. (1998), this is defined as $2 \times (Credit_t + Credit_{t-1})/(Credit_t - Credit_{t-1})$, and allows firms to transition in and out of borrowing without affecting the sample. The results for the regressions of credit growth on bank failure show that even when the measure is taken as credit growth, the response is driven by firms borrowing via relationships rather than collateral. Specifically, bank failures are associated with a 0.3 percentage point decline in credit growth for all firms, and a 0.4 percentage point decline for relationship-dependent firms. Similar to the results from specifications where the outcome variable is $Log(Credit)$, the coefficient from the regression of credit growth on bank failure for collateral-dependent firms is not significant.

In Columns (7)-(9) of Panel B, I scale the outcome variable and measure credit as a share of the firm's sales. The coefficients for the regression with outcome variable as $Log(Credit_{it}/Sales_{it})$ are in line with the previous results. In Column (7), the average decline in credit for firms is -0.616 (a decline of 46% in the credit to sales ratio), significant at the 1% level. In Column (8), for collateral-dependent firms the coefficients are relatively

[15]That is, it is listed in the categorization following the online appendix of Mian and Sufi (2014)

[16]In the Online Appendix, I examine firms which are in industries with high external dependence of finance (Rajan and Zingales, 1998). I find credit for firms in these is more sensitive more to bank failures, consistent with the literature (Duygan-Bump et al., 2015; Barone et al., 2018). In my context, relationship-dependent firms that have high external dependence show even higher sensitivity to bank failures.

[17]Small firms do not borrow every quarter. This is consistent with the lumpy adjustments for capital and longer term investments by firms seen in the literature (Bloom et al., 2007).

smaller and insignificant. Following the results in the rest of the table, the coefficient for relationship-dependent firms is higher at -0.658. This is significant at the 1% level, and corresponds to a decline of 48% in the credit-to-sales ratio following bank failure.

Table 2: Bank failure and firm credit: regression results

Panel A: Firm credit and bank failure controlling for demand

	Log Credit								
	All	Collateral dependent	Relationship dependent	All	Collateral dependent	Relationship dependent	Relationship dependent		
							All Inds	All Inds -Constrn	All Inds -Constrn -Non-trad
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bank Failure	-0.275***	-0.096	-0.291**	-0.295***	-0.035	-0.362***	-0.234*	-0.264**	-0.266**
	(0.105)	(0.089)	(0.128)	(0.101)	(0.089)	(0.133)	(0.127)	(0.132)	(0.134)
Demand Index	-0.006	0.013	-0.013						
	(0.028)	(0.021)	(0.033)						
Fixed effects:									
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Qtr-County				Yes	Yes	Yes			
Quarter FE's							Yes	Yes	Yes
Obs	229,715	136,355	91,045	222,480	129,706	84,053	91,293	82,161	74,649

Panel B: Firm credit and bank failure: alternative frequency & credit measures

	Log Credit			Credit Growth			Log(Credit/Sales)		
	All	Collateral dependent	Relationship dependent	All	Collateral dependent	Relationship dependent	All	Collateral dependent	Relationship dependent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bank Failure	-0.563***	-0.061	-0.716***	-0.344**	0.223	-0.446**	-0.616***	-0.229	-0.658***
	(0.177)	(0.133)	(0.228)	(0.159)	(0.175)	(0.195)	(0.193)	(0.198)	(0.243)
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Cty	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	84,657	51,764	32,893	40,424	20,694	19,730	67,470	38,925	28,545

Notes. Bank failure and firm credit. Bank Failure is an indicator which equals value 1 in the quarter of bank failure and 6 subsequent quarters in Panel A, and value 1 in the year of bank failure and the subsequent year in Panel B. The demand index is constructed at the firm-quarter level using customer locations. Credit is the sum of all transactions categorized as new long-term liabilities to the firm. The categorization of tradability follows the online appendix of Mian and Sufi (2014). Column (8) excludes construction industries, Column (9) excludes construction and non-tradable industries. Credit growth is defined following Davis et al. (1998) as $2 \times (Credit_t - Credit_{t-1})/(Credit_t + Credit_{t-1})$. Regressions are weighted by firm employment. Dependent variables are winsorized at the top and bottom 1%. Standard errors are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.4 Selection effects

Table 3: Selection effects

Panel A: Balance in 2006	Failures	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
Income	1068	1326	0.112	0.163
Expenses	7228	885	0.2663	0.277
Trade credit	186	330	0.1628	0.104
Transactions	7712	8215	0.623	0.922
Employment	12.26	12.54	0.819	0.695
Log Employment	1.86	1.95	0.145	0.322

Panel B: Placebo test: six quarters prior to bank failure	Log(Credit)					
	All	Collateral dependent	Relation dependent	All	Collateral dependent	Relation dependent
	(1)	(2)	(3)	(4)	(5)	(6)
Bank Failure - 6 quarters	0.097	-0.042	0.018	0.069	-0.040	0.098
	(0.112)	(0.090)	(0.130)	(0.116)	(0.098)	(0.144)
Demand Index	-0.066*	-0.035	-0.071*			
	(0.036)	(0.027)	(0.040)			
Fixed effects:						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Qtr-County				Yes	Yes	Yes
Firm-Qtr Observations	132,451	62,123	69,433	137,133	65,717	71,416

Notes. Panel A shows the results from balancing tests between firms that faced bank failures and firms which did not, for values of key variables in 2006. Income, expenses and trade credit are reported in thousands of dollars, transactions is rounded to the nearest whole number. Differences in p-values calculated directly as well as with county and 2 digit industry fixed effects. Panel B shows a placebo test for the response of firm credit to bank closure measured six quarters before bank failure. Credit is measured as the sum of all long term liabilities to the firm, winsorized at the top and bottom 1%.

The regression results of Table 2 may be confounded by selection effects. It may be possible that the small business portfolio of banks which fail is ex-ante different from the portfolio of healthy banks. If the affected firms have lower credit demand or poorer performance when the bank was relatively healthy "pre-treatment", then this difference may be driving a part of the relationship between credit and bank failure. In this scenario, the estimated coefficient β in equation 2 will overstate the magnitude of disruption in credit arising from the dissolution of the lending relationships.

To check for selection, I first compare whether firms which faced bank failures were different from firms which did not, based on observable characteristics measured in 2006. In 2006 the lender is relatively healthy, so lower loan volumes are more likely to reflect credit demand. This is prior to the bank failures used in the analysis from the FDIC failed bank list 2007-2013.[18] Panel A of Table 3 shows the difference in the mean values of credit, log of credit and the log of the credit to sales ratio for firms which later faced bank failure versus those which did not. The table shows the results of t-tests for the differences of these means. As we can see, there is no significant difference, as seen in the p-values of these tests. I also compare the conditional means of credit across the affected and unaffected firms *within* industry and

[18]The largest share of bank failures for firms in the dataset occured in 2008 and 2009. Thus for most firms, these variables are measured approximately 2 or 3 years prior to bank failure, when banks are not facing imminent failure or extreme distress.

region, through an OLS regression with an indicator if firms later faced bank failure, where I control for 2 digit industry and county fixed effects. The corresponding p-values on the indicator for failure are reported in the table. As we can see, there is still no significant difference in credit between the two sets of firms. In addition to credit, I compare firm performance measured through income, expenses, trade credit, the number of transactions, employment and log of employment. Again, I do not find any statistical difference between affected and unaffected firms, either with t-tests without controls, or with controls for industry and region, suggesting that firms affected by bank failure neither had lower credit demand, nor poorer performance prior to the Financial Crisis.

The second check for selection is a placebo test for 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. In order to check whether this is the case, I shift the indicator for bank failure back by one and a half years to test this. For example, if a firm faced bank closure in 2008, the original indicator for failure in the annual data took value 1 in 2008 and 2009. The placebo 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 findings in Table 2 may be driven by selection. The results from the placebo test are shown in Panel B of Table 3. Columns (1)-(3) uses controls for demand shocks using the demand index, on the full sample, collateral-dependent firms, and relationship-dependent firms. Columns (4)-(6) show the results from the placebo test with controls for demand shocks using fixed effects. I do not find significant differences in credit prior to bank failure in any of the cases, either for the full sample (Columns (1) and (4)), or for collateral-dependent firms (Columns (2) and (5)) or for relationship-dependent firms (Columns (3) and (6)). Along with the balance tests in Panel A, the placebo test confirms that selection effects are not driving the results described in Table 2.

To summarize the results in this section, I show that the sensitivity of small business credit to bank failures last upto six quarters, and are driven by firms predominantly dependent on lending relationships. These results hold while controlling for firm-level characteristics using fixed effects, and while controlling for contemporaneous demand shocks using different strategies. They are also robust to a variety of specifications, including including changing the definitions of collateral-dependent and relationship-dependent firms.[19] The recovery of firm credit after six quarters suggests that the affected firms were not adversely selected. The results suggest there are distinctions between firms which are relationship-dependent and collateral-dependent in the impact of bank failure. Firms which borrow on the basis of collateral, can pledge the their collateral to other lenders in the event of their bank's failure, and maintain previous levels of credit. However, such firms may instead be affected by movements in collateral prices, while relationship-dependent firms would be less sensitive to real estate price movements. I analyze this in the next section.

4 House prices and firm credit

4.1 Empirical strategy

Business owners often use their personal collateral as a pledge for business loans, and access additional credit as the value of the collateral rises. Large fluctuations in house prices may affect the ability of small business owners to access credit. I quantify the sensitivity of firm credit to house prices across time both for collateral-dependent firms as well as relationship-dependent firms. Similar to the situation in Section 3, the regression coefficient β of $Log(Credit)$ on the house price index will suffer from an upward bias if I omit to account for credit demand. To control for such demand shocks, I use the firm-level index Dem_{it} defined in equation 1 to control for demand.[20] With this, I isolate the role of credit supply through the

[19]See Section A.2 of the Online Appendix for further details.

[20]Note that using data on addresses of the owner versus the customers of a firm allows me to distinguish between house price movements at the business owner's home location and house price movements in the firm's customer locations.

collateral-lending channel. I estimate the following equation:

$$Log(Credit_{it}) = \beta Log(ZHVI_{zt}) + \gamma Dem_{it} + f_i + e_{it} \tag{3}$$

where $Log(Credit_{it})$ is the log of the credit, measured as the sum of all long-term liability transaction *to* the firm) of firm i in time period t, $ZHVI_{zt}$ is the Zillow Home Value Index matched to the ZIP code of the owner's home address. All specifications include firm fixed effects f_i to account for any unobservables at the firm-level. Standard errors are clustered at the zip code level to control for residual correlations across observations in the same location.

An alternative strategy I use to control for demand shocks uses county-quarter fixed effects, following developments in the literature (Acharya et al., 2019; Degryse et al., 2019). This controls for any local economic shocks that simultaneously affect credit demand arising from increases in consumer demand, as well as credit supply, through increases in the entrepreneur's personal housing wealth. The identifying assumption in this case is that firm credit varies with house price movements at the home zipcode of the owner, while demand shocks are more geographically dispersed, varying only at the county level.

Table 4: Firm credit and house prices

Panel A: Firm credit and house prices across firm size

	Log(Credit)					
	All	Collateral	Relationship	All	Collateral	Relationship
	(1)	(2)	(3)	(4)	(5)	(6)
Log(ZHVI)	0.332***	0.329***	0.272*	0.219**	0.308**	0.077
	(0.059)	(0.086)	(0.150)	(0.099)	(0.137)	(0.152)
Demand Index	-0.007	-0.018	-0.014			
	(0.009)	(0.014)	(0.028)			
Fixed effects:						
Qtr-County				Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Observations	439,755	236,611	199,211	438,238	233,016	195,738

Panel B: Firm credit and house prices with tradability (collateral-dependent)

	Log(Credit)		
	All	All -Construction	All -Construction -Non-tradables
	(1)	(2)	(3)
Log(ZHVI)	0.395***	0.390***	0.371***
	(0.075)	(0.079)	(0.081)
Fixed effects:			
Quarter	Yes	Yes	Yes
Firm	Yes	Yes	Yes
Observations	250,935	225,980	207,248

Notes. The correlation between firm credit and house prices. Credit is the sum of all long-term liabilities issued to the firm in a given quarter, winsorized at the top and bottom 1%. Panel A: The demand index is constructed at the firm-quarter level using customer locations. Panel B: The categorization of industries on tradability follows the online appendix of Mian and Sufi (2014). Column (2) excludes construction industries, Column (3) excludes construction and non-tradable industries. Standard errors are clustered at the zip code level.

4.2 Results

Table 4 shows the results from estimating equation 3 at the quarterly level. The coefficient of interest is β, which can be interpreted as the change in credit associated with a 1% change in the median house price in the zip code. In Panel A, I begin in Columns (1)-(3) with estimating the relationship between house prices and firm credit with the firm-level demand index and firm fixed effects. Column (1) shows the specification from equation 3 for all firms in the sample. The coefficient is 0.332, significant at the 1% level. As this is a regression of log(credit) on the log of the house price index, this can be interpreted as a 0.33% change in firm credit when there is a 1% change in house prices. When the sample is split into collateral-dependent and relationship-dependent firms, it becomes clear that the coefficient on the first group is higher than that for the second, with a value of 0.329 relative to 0.272. In Column (3), for the subset of relationship-dependent firms, the coefficient is smaller. [21]

In Columns (4)-(6), I estimate the relationship between credit and house prices controlling for consumer demand by using County-Quarter fixed effects. Similar to the results from Columns (1)-(3), there is a positive relationship between the Zillow Home Value Index and credit, with a 1% increase in the median house price associated with a 0.2% increase in credit. Once again, the result are driven by collateral-dependent firms, for whom the coefficient β is higher at 0.31, while the relationship for relationship-dependent firms shows both a lower coefficient at 0.08, which is not statistically significant.

I further confirm the results by limiting the analysis to firms in 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. This strategy follows Adelino et al. (2015) where tradable industries are used to isolate the collateral-lending channel. The intuition goes as follows: if the credit of firms is positively associated with house prices on the subsample of firms in tradable industries, it suggests the relationship between local house prices and credit is not driven only by demand. Instead, if the results do not withstand removing firms in non-tradable industries from the sample, it would suggest that the relationship between house prices and firm credit is primarily because of the demand channel. The results from the estimation of 3 using tradability across industries to separate demand shocks from credit shocks are shown in Panel B of Table 4, where I run the estimation on the subset of collateral-dependent firms. Column (1) shows the regression of $Log(Credit)$ on house prices for firms in all sectors for which tradability measures are available, controlling only for quarter and firm fixed effects. In this case, the coefficient β is significant with a coefficient of 0.395. In Column (2), where firms in the construction industry are removed from the sample, the coefficient still remains significant as well as similar in magnitude at 0.390. 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 at the 1% level and similar in magnitude, at 0.371. Since the effect for firms in tradable industries remains significant and positive, as well as relatively stable across the columns in magnitude, this further suggests a role for credit supply through the housing channel, with magnitude above 0.3%.

In addition to the strategies for demand controls described above, I confirm in Table A2 in the Online Appendix that firms with high external dependence on finance (based on the measure by Rajan and Zingales (1998)) show greater sensitivity to firm credit. For firms which borrow through collateral and are also highly dependent on external financing, the results are even more pronounced.

My estimates for the sensitivity of firm credit for collateral-dependent firms at 0.3% change in credit with a 1% change in local housing value are in line with the literature. Kleiner (2014) studies firms' response to collateral price movements in the UK, finding firms extract $0.25 of debt for every $1 increase in real estate value.[22] The comparative effects for public firms are much smaller: Chaney, Sraer, and Thesmar (2012)

[21] Note that it is feasible for relationship-dependent firms to also be sensitive to house price movements but to a lesser extent, if they partially satisfy their higher credit requirements using personal housing assets as collateral.

[22] On the household side, Mian and Sufi (2011) find that the average US homeowner extracts $0.25-0.30 for each dollar of

find that a $1 appreciation in a firm's real estate value increases investment by approximately $0.06.

5 Robustness of results

A potential threat to the results is that firms in the sample that link bank accounts are different from firms that do not. In this case, the selection of firms into the sample for which I can estimate the impact of bank failures may be driving the difference in results of collateral-dependent and relationship-dependent firms towards the two types of credit shocks. I compare the two sets of firms in the baseline sample of 141,678 versus the subset of 77,124 firms of these which have linked banks. I compare the firm on various characteristics, focusing on factors that may be correlated with linking the business bank account with the software. The results for the comparison across samples are shown in Table A3 in the Online Appendix, where I find the two samples are not different on observable characteristics. There may be unobservables not captured in Panel A of Table A3 that are different for firms across the two samples. In Panel B of the table, I restrict the estimation to the sample to firms for which I observe banking relationships. The coefficients are similar in magnitude and significance to the results shown in Section 4. The relationship of credit with house prices remains significant for collateral-dependent firms, with 0.3% higher credit associated with a 1% increase in the house price index. The magnitudes of both coefficients for relationship-dependent firms are slightly smaller than those found in comparable specifications for collateral-dependent firms, following the results in Table 4. The results in Table A3 thus suggest that selection of different firms into linking business bank accounts to the software is not driving the difference the impact of the two credit shocks.

Bank failures and house price movements may both be driven by local economic shocks during the Great Recession. In estimating the effect of each shock separately, I may not be taking into account the correlation between the two, arising from omitted variables. In Table A4 of the Online Appendix, I study the simultaneous impact of the two shocks. When estimating the impact of the two shocks simultaneously for the two sets of firms, I find, as in Section 3 and Section 4, that collateral-dependent firms show significant sensitivity to house price movements and not to bank failures, while the credit of relationship-dependent firms varies with bank failures but not with house price movements. This reiterates the differential impact of shocks depending on how different small businesses eased financial constraints.

new home equity.

6 Discussion and Conclusion

In this paper, I quantify the credit effects of bank failures and house price movements on small businesses during the Great Recession, using transactions-level data on a representative sample of small businesses in the US. I aggregate credit data for more than 140,000 small businesses in the US, and link firms to bank failures and house price movements. Controlling for demand shocks at the firm level, I find that while bank failure leads to a significant average decline of 25% in new credit to relationship-dependent firms, the effect is smaller and non-significant for collateral-dependent firms. For affected firms, the effects last for 6 quarters, after which credit recovers, suggesting that that the channel for the impact is asymmetric information. On the other hand, I find that the credit of firms predominantly dependent on collateral varies with house price movements, with a 1% change in the median house price in the business owner's zip code associated with a 0.3% change in credit. The coefficient for relationship-dependent firms is smaller as well as non-significanct. These results are consistent with small business survey data, which suggests there are differences even within the small business universe in how firms ease financing constraints.

This paper primarily contributes to a large empirical literature on the effects of credit shocks on small businesses during the Great Recession. To the best of my knowledge, this is the first attempt to quantify the financial effects of house price *and* banking shocks at the firm-level on a representative sample of small businesses during this period, and thus the first to reveal heterogeneity in the impact of these two credit shocks across firms within the small business universe. I estimate the magnitude of impact for these two shocks at the firm level, with relationship-dependent firms experiencing declines of 25% following bank failures, and collateral-dependent firms extracting 0.3% credit from each 1% change in collateral value. This paper make a case for incorporate heterogeneities in the sources of borrowing into existing models of financial frictions. This paper also sheds light into the role of soft and hard information for small business borrowing: while the IT revolution in banking in recent decades, bank failures still lead to disruptions in credit for small firms for up to one and a half years.

The empirical findings also have important implications for policy, especially in the context of bank bailouts. One dimension of the debate on bailouts is the impact they have on small business credit access (Giannetti and Simonov, 2013). The results in this paper suggest that for firms which borrow using collateral, switching lenders may be relatively easy, limiting the impact of a bail failure on credit access. This can inform cost-benefit analyses of a bailout decision. Moreover, the paper highlights the importance of credit registries. Credit registries are available in many countries but still absent in the United States (Mian, 2014). Shared information can reduce the impact of bank failures on firm credit by facilitating switches to healthier lenders (Choudhary and Jain, 2020). The decline in small firm credit for one and a half years following a bank failure suggests credit registries are especially important during periods of economic downturn. Furthermore, a credit registry can also facilitate firm borrowing based on business value and credit worthiness rather than rely on personal wealth.

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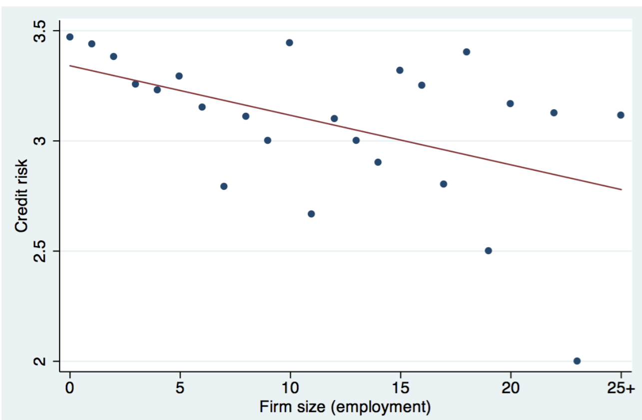
A Appendix: For Online Publication

A.1 Collateral vs. Relationship dependence

Even within the small business universe, there may be differences in access to credit via these two sources. In Figure A.1, I use data from the Kauffman Firm Survey (2004), and show the relation between credit risk and firm size within small businesses. The figure shows that credit risk decreases with firm size. This is consistent with the literature on the costs of relationship lending. As a consequence, lenders may be less willing to give uncollateralized credit to the very small firms. Survey data suggests the basis of borrowing is related to firm size. Using data from the National Survey of Small Business Finances (2003), I find that for firms with less than or equal to 10 employees, 27% of collateralized lines of credit is through mortgages while those with more than 10 employees have a share of 13%. In contrast, businesses with more than 10 employees have 29% of credit based on business valuations while those with less than or equal to 10 have only 9%.

Figure A.1: Firm size and sources of borrowing



Source	Micro	Small
Housing collateral	27%	13%
Value of business	9%	29%

Notes. The left panel shows the average credit risk across firm size from Kauffman baseline (2004) survey: Credit risk is based on percentiles of commercial credit scores. Firm employment is sum of all part time and full time workers on payroll (exclude contract workers) at the end of the calendar year. The right panel shows sources of credit split across firms with less than or equal to 10 employees) and firms with more than 10 employees, from the Survey of Small Business Finances (2003). Housing collateral is an indicator variable which takes value 1 if firms report taking credit based on collateralized lines of credit through mortgages. Value of business is an indicator variable which takes value 1 if firms report borrowing based on business valuations.

A.1.1 Robustness to definition of relationship-dependence

In Table A1, I check that the differences in results found in Table 2 are robust to changing the cutoff of 10 employees that is used to define collateral-dependent versus relationship-dependent firms. In Columns (1) and (2), I change the cutoff from 10 employees to 5 and in Columns (3) and (4), I change it instead to 15 employees. In Columns (1) and (2), compared to the similar specification in Columns (2) and (3) of Panel A in Table 2, we can see that the coefficient for collateral-dependent firms continues to be insignificant, while for relationship-dependent firms it is slightly lower at -0.316, and significant at the 1% level. In Columns (3) and (4) with a size cutoff of 15 employees, the coefficient of log credit on bank failure is again insignificant for collateral-dependent firms. The coefficient is slightly higher in this case for relationship-dependent firms at -0.382, and again significant at the 1% level. Firms which are older may have more shared information with lenders, or a higher ability to show codified information, for example, through longer credit histories. This raises the concern that the difference in sensitivities of credit to bank failure for relationship-dependent firms versus collateral dependent firms Table 2 may be driven by differences in firm age rather than the definition I use, based on firm size. To check if this is the case, in Columns (7)-(9), I control for firm age to separate the effects. While older firms have lower declines in credit relative to younger ones, as can be seen in the coefficient of $Log(Credit)$ on $Log(Age)$, the coefficient on bank failure remains negative and significant with similar magnitude at -0.305 and -0.372 overall and for relationship-dependent firms respectively, both significant at the 1% level. This suggests that even when we take firm age into account, the classification using firm size is still valid.

Table A1: Firm credit and bank failure: robustness to firm size measures

	Log Credit								
Employees:	Coll	Reln	Coll	Reln	Coll	Reln	All	Coll	Reln
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bank Failure	0.052	-0.316***	-0.135	-0.382***	0.049	-0.363***	-0.305***	-0.013	-0.372***
	(0.116)	(0.108)	(0.083)	(0.148)	(0.092)	(0.129)	(0.101)	(0.094)	(0.131)
Log(Age)							0.046	0.101**	0.025
							(0.063)	(0.045)	(0.089)
Fixed effects:									
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Qtr-County	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	74,705	161,085	166,019	69,771	118,862	116,928	224,827	125,958	98,869

Notes. Bank failure and firm credit regression results. Bank Failure is an indicator which equals value 1 in the quarter of bank failure and 6 subsequent quarters. Credit is the sum of all transactions categorized as new long-term liabilities to the firm. In Columns (1)-(3), the employment cutoff for collateral-dependent and relationship-dependent firms is 5, and in Columns (4)-(6) it is 15. Firm age is years between the current year in the panel and the minimum of the firm's year of establishment from Dun and Bradstreet and the first year of registration in the software. Credit growth is defined following Davis et al. (1998) as $2 \times (Credit_t - Credit_{t-1})/(Credit_t + Credit_{t-1})$. Regressions are weighted by firm employment. Dependent variables are winsorized at the top and bottom 1%. Standard errors are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.2 Additional results

A.2.1 External dependence on Finance

Firms which have higher dependence on external sources of financing may be affected more by credit supply shocks relative to the average firm (Duygan-Bump et al., 2015; Barone et al., 2018). I account for the extent of external financing with 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. To study how external financing interacts with the impact of credit supply shocks, I estimate effects for the subsample of firms that are in the top and bottom quartiles of the external dependence measure based on Rajan and Zingales (1998)[23]. For all subsets of the sample, I control for County-Quarter and 2-digit NAICS Industry fixed effects. Standard errors are clustered at the firm level.

Table A2: External dependence on finance

Panel A: Bank failure and firm credit				
	Log(Credit)			
	All		Relationship dependent	
	Low Ext. Dep.	High Ext. Dep.	Low Ext. Dep.	High Ext. Dep.
	(1)	(2)	(3)	(4)
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
Panel B: House prices and firm credit				
	Log(Credit)			
	All		Collateral dependent	
	Low Ext. Dep.	High Ext. Dep.	Low Ext. Dep.	High Ext. Dep.
	(1)	(2)	(3)	(4)
Log(ZHVI)	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 supply 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). Credit is measured as the sum of all transactions categorized as long-term liabilities to a firm. Bank failure is an indicator variable that equals 1 for the quarter the firm faces bank failure and the following 6 quarters. The Zillow Home Value Index (ZHVI) is the measured 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 restricted to the firms with bank linkages. Regressions with bank failure are weighted by firm employment. All columns include controls for County-Quarter and 2-digit NAICS Industry fixed effects. Standard errors are clustered at the firm level.

The results are shown in Table A2. In Panel A, I find higher coefficients of credit on bank failure for firms in industries with high external dependence on finance versus firms in industries with low external dependence on finance, consistent with the literature on banking supply shocks Duygan-Bump et al. (2015); Barone et al. (2018). The coefficient in Column (1) for the subset of firms with low external dependence is not significant, while the coefficient in Column (2) for the subset of firms with high external dependence on finance is -0.511. This corresponds to an 40% percent change in credit of the firm following bank failure for firms with high external dependence. The result is stronger for relationship-dependent firms: In Column (3), the coefficient is not significant but it is higher in magnitude relative to Column (1), at -0.312. Column (4) shows the response to bank failure for relationship-dependent firms with high external dependence on finance. This column has the

[23]The original measure is defined over SIC 2-digit codes. I convert SIC2 digit industry codes to NAICS 2-digit industry codes using the 1997 vintage of the US Census crosswalk. For each SIC2 for which I have the measure of external dependence, I assign the measure to all NAICS2 it corresponds to in the crosswalk. I exclude all NAICS industries that match to multiple SIC codes.

highest coefficient at -0.601 significant at the 1% level, corresponding to a 45% decline in credit following bank failure for firms in industries with high external dependence on finance.

In Panel B, I examine the relationship between house price movements and firm credit for firms in industries with low versus high external dependence on finance, I find in Columns (1) and (2) that firms in industries with high external dependence on finance show higher sensitivity to collateral price movements (coefficient on log(ZHVI) equals 0.172 versus 0.154). The difference is even starker for collateral-dependent firms. In Column (3), for firms with low external dependence on finance, the coefficient is not significant, while in Column (4), for collateral-dependent firms with high external dependence on finance, the coefficient is larger at 0.217 and significant at the 1% level. Thus, my results show that firms which have higher dependence on external sources of financing are affected more by both kinds of credit supply shocks.

A.2.2 Robustness to sample selection

Firms that report banking relationships may be different from firms that do not. In this case, selection of firms into the sample which links banks may be the reason for the difference in response for the two sets of firms towards the two credit shocks. To examine if this is the case, I compare collateral-dependent and relationship-dependent firms in the baseline sample of 141,678 and the subset of 77,124 firms of these which have linked banks on characteristics which could influence linking the bank account with the software. I first consider factors which suggest that firms are more or less dependent on borrowing using personal collateral versus information sharing with banks: age, dependence on external financing and legal form. Older firms have credit histories and may be able to engage with banks for relationship-based lending. Similarly, firms which are in industries with high dependence on external financing may have better access to bank-based financing. The organization structure of the firm may also matter: owners of limited liability companies may be more likely to raise credit from housing assets due to lower downside risk relatively to other organizational forms. The results for the comparison across samples are shown in Panel A of Table A3. As we can see, there is only a year of difference in the age of collateral-dependent versus relationship-dependent firms across the samples. The distribution of firms in the two samples across sectors are also comparable. For various kinds of company structure, the distribution of firms across the samples are also similar.

There may be unobservables not captured in Panel A of Table A3 that are different for firms across the two samples. In Panel B of Table A3, I estimate equation 3 on the restricted sample to firms for which I observe banking relationships. The coefficients are similar in magnitude and significance to the results shown in Section 4: the relationship of credit with house prices remains significant for collateral-dependent firms, with a 1% increase in the house price index associated with 0.3% higher credit, as shown in Columns (1) and (2). The estimated coefficient for collateral-dependent firms in Columns (3) and (4) shown slightly higher magnitudes, with 1% change in house prices associated with a 0.42% change in firm credit, when controlling for firm fixed effects in Column (4). Columns (5) and (6) show that the relationship between credit and house prices is also significant for relationship-dependent firms in the specification with industry fixed effects. It is feasible that relationship-dependent firms may also be sensitive to house price movements if they partially satisfy their credit requirements using personal housing assets as collateral. However, the relationship is no longer significant once I introduce firm fixed effects into the regression. Together, Panels A and B of Table A3 suggest that selection into linking banks to the software is not driving the results.

A.2.3 Simultaneous estimation of the two shocks

Bank failures and house price movements may have both been driven by local economic shocks. For this reason, I also study the simultaneous impact of banking and housing shocks together.

The results are shown in Table A4. Column (1) estimates the impact of both shocks for the full sample. The relationship between credit and bank failures as well as house prices appears significant, suggesting both channels play a role for firm credit. However, in Column (2) I include firm fixed effects and the coefficient on the house price index is similar in magnitude as Column (1) but not longer significant. In the subsequent columns, I estimate the specification of Column (2) for collateral-dependent and relationship-dependent firms separately. In Column (3), the coefficient of 0.220 is significant at the 1% level on the log of the house price index for collateral-dependent firms. This coefficient is similar to the coefficient on house prices found in Table 4. In contrast, the coefficient on bank failure for these firms is smaller in magnitude at -0.059 and it is not significant. This confirms collateral firms are sensitive to house price movements with a change of 0.2% in credit with 1% change in collateral value, but for them, bank failures affect credit less. Column (4) is similar to Column (2) but for relationship-dependent firms. In this case, I find a large coefficient of -0.328 significant at the 1% level on bank failure and a smaller and insignificant coefficient of 0.148 on the house price index. The magnitude is similar to the magnitudes using fixed effects to control for demand in Table 2. Table A4 supports the results of differential impact of shocks arising from differences in how small firms can access finance.

Table A3: Sample Selection

Panel A: Comparison of overall sample & subset with bank linkages

	All		Collateral dependent		Relationship dependent	
Sample:	House prices	Bank Failures	House prices	Bank Failures	House prices	Bank Failures
Age:						
Mean	10.03	8.38	8.43	7.14	12.46	10.56
Median	6	5	5	4	8	7
Sector (%):						
Agriculture	1.23	0.88	1.10	0.77	1.37	1.09
Construction	7.99	8.25	8.22	8.21	7.76	8.29
Manufacturing	4.83	4.12	5.05	4.14	4.61	4.08
Retail	7.39	7.18	7.83	7.00	6.95	7.47
Service	67.44	75.67	72.69	75.66	62.10	75.55
Wholesale	4.03	3.75	4.79	4.00	3.25	3.28
Other	0.27	0.16	0.24	0.15	0.31	0.17
Legal form (%):						
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
Partnership/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
Other	46.48	61.26	46.34	46.91	48.18	49.15

Panel B: Estimation of equation 3 on subsample with bank linkages

	Log(Credit)					
	All	All	Collateral dependent	Collateral dependent	Relationship dependent	Relationship dependent
	(1)	(2)	(3)	(4)	(5)	(6)
Log(ZHVI)	0.200***	0.376***	0.216***	0.420***	0.226***	0.130
	(0.034)	(0.098)	(0.037)	(0.140)	(0.055)	(0.146)
Demand index	-0.033	0.019	-0.030	-0.016	-0.009	0.044*
	(0.029)	(0.017)	(0.033)	(0.023)	(0.045)	(0.025)
Fixed effects:						
Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes		Yes		Yes	
County	Yes		Yes		Yes	
Firm FE's		Yes		Yes		Yes
Observations	180,312	175,668	105,518	100,718	74,766	73,120

Notes. Panel A: Comparison for quarterly samples used in Sections 3 and 4. Panel B: Estimation of equation 3 on the restricted sample with bank linkages. Credit is measured as the sum of all transactions categorized as long-term liabilities to a firm. Bank Failure is an indicator variable that equals 1 for the quarter the firm faces bank failure and the following 6 quarters. ZHVI is the Zillow Home Value Index (ZHVI) at the ZIP code of the owner's address, averaged over months in the quarter. The demand index is constructed using house price variations in the firm's customer zip codes weighted by customer shares. Industry is 2-digit NAICS sector. Standard errors are clustered at the zip code level.

Table A4: Banking and housing shocks: simultaneous effects

	Log(Credit)			
	All	All	Collateral dependent	Relationship dependent
	(1)	(2)	(3)	(4)
Bank Failure	-0.558***	-0.292***	-0.059	-0.328***
	(0.107)	(0.098)	(0.072)	(0.116)
Log(ZHVI)	0.188***	0.213	0.220***	0.148
	(0.029)	(0.137)	(0.109)	(0.161)
Demand Index	-0.081***	0.004	-0.014	0.002
	(0.029)	(0.032)	(0.024)	(0.037)
Fixed effects:				
Quarter	Yes	Yes	Yes	Yes
Industry	Yes			
County	Yes			
Firm		Yes	Yes	Yes
Observations	180,312	175,668	100,718	73,120

Notes. Bank Failure is an indicator variable that equals 1 for the quarter the firm faces bank failure and the following 6 quarters. House price measure is log of the Zillow Home Value Index (ZHVI) at the ZIP code of the owner's address, averaged over months in a quarter. The sample is restricted to firms which have bank linkages in the software. Industry is 2-digit NAICS sector.

A.3 Data: Sample construction and representativeness

The baseline sample used in the analysis is constructed as follows. First, I first take companies from the software based in the US (requiring address information), and which have had a paid subscription beyond the free trial period. I also exclude duplicate firms and companies flagged to have data issues. I further restrict to firms for which I am able to match the data to Dun and Bradstreet. From these, I exclude accounting firms (NAICS 5412), which may be handling multiple companies under one account, firms in non-classifiable industries (NAICS 99) and non-profits.[24] The baseline sample thus constructed consists of 141,678 firms. This is used in the analysis for house price movements. Of these, 77,124 firms import their transactions into the software from their business bank accounts. This is the subsample used for analyzing the impact of bank failures on firm credit.

I examine whether the distribution of firm size in the sample represents that of the US firm population. Table A5 shows the distribution of firms in the sample and the population of US employer firms across standard size bins in 2010.For both the sample and the population, there is a high concentration of firms at the lower end of the size distribution. Approximately 80% of firms have less than 10 employees in the population, which is about 70% in the sample. Another 12-14% have 10-20 employees, and less than 2% firms have more than 100 employees in both the population and the sample.

Table A5: Representativeness across firm size

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

Notes. Mid-March employment shares in the sample and the population (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 back-end data of the payroll register of the software, documenting hiring and release dates of employees for 2010 (total number of firms is 76,918).

I also compare the distribution of firms in the sample and the population across broad as well as narrow NAICS industries. The comparison is shown in Table A6. 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 involved in manufacturing.[25] The sample industries are also representative of the population at narrower-definitions using the NAICS classification.

[24]Non-profit NAICS codes: 6100, 6115, 6200, 6241, 7121, 8131-8134, 8139, 9221, 9241 and 9251.

[25]For evaluating industry representativeness, I restrict the comparison to firms with less than 500 employees.

Table A6: Representativeness across sectors

Sector(1 digit NAICS)	Share (% sample)	Share (% population)
Service	77.00	70.91
Retail	7.85	11.97
Construction	9.01	11.44
Manufacturing	4.68	4.87
Mining	0.24	0.43
Agriculture	1.19	0.38

Notes. Distribution of firms across 1 digit NAICS Sectors for the sample and the population (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" are excluded from the tabulation.

Table A7: Representativeness across industries

Industry(2 digit NAICS)	Share (% sample)	Share (% population)
Professional services	22.75	14.14
Retail trade	7.85	11.97
Other services	5.11	11.96
Health care	11.23	11.50
Construction	9.01	11.44
Accommodation and food	4.84	8.94
Waste management	12.95	6.03
Real estate	3.41	4.93
Manufacturing	4.68	4.87
Finance	4.01	4.45
Transportation	2.80	3.22
Arts and recreation	2.66	2.07
Education	2.90	1.54
Information	3.95	1.41
Management	0.26	0.60
Mining	0.24	0.43
Agriculture	1.19	0.38
Utilities	0.13	0.12

Note: Distribution of firms across 2 digit NAICS Industries for the sample and the population (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" are excluded from the tabulation.