Financial crises and filling the credit gap: the role of government-guaranteed loans

ABSTRACT:

I ask whether and how the local availability of Small Business Administration (SBA) 7(a) guaranteed loans encouraged lending to small firms during the recent financial crisis when they were particularly constrained. I find that areas with a greater proportion of SBA lenders during the crisis not only had higher small business loan volume, but also saw increased employment and establishments, but only for the smallest firms. The findings suggest that targeted government support to small firms can potentially play a beneficial role in the recovery of local regions in the presence of private credit market frictions.

"Making credit accessible to sound small businesses is crucial to our economic recovery and so should be front and center among our current policy challenges."

-Ben Bernanke "Addressing the Financing Needs of Small Businesses," (July 12, 2010)

Recent research and policy focus on small business credit access in the wake of the financial crisis largely stems from the belief that small firms are the engine of economic growth.[1] It also comes as a response to the drastic drop in small business lending, which decreased by 18% from 2008-2011 relative to 9% for total business lending (Cole (2012)). The disparate decline in small business lending is particularly troubling given that small firms rely heavily on banks for financing. If, therefore, small firms were disproportionately cut off from financing during the crisis, then tightening financial constraints could help to explain the somewhat anemic recovery through their restrictive effect on these important producers and job-creators. The above quote from Federal Reserve Chairman Ben Bernanke shows that policymakers do indeed recognize the importance of credit provision to small firms for economic growth, and that the provision of credit to small firms represents a central policy concern. I ask in this paper whether and how policymakers can intervene in credit markets to ease financial constraints for small businesses during crises, and whether this can in turn translate to better real outcomes.

To address this question I focus on a particular type of indirect intervention into small business credit markets: partial credit guarantees. In the US, the largest and longest running government program aimed at providing capital to small businesses is the Small Business Administration's 7(a) Guaranteed Lending Program. The purpose of the program is to help "creditworthy small businesses acquire financing when they cannot otherwise obtain credit at reasonable terms" (OCC (2015)).[2] In this program, participating lenders provide loans for

[1] A brief look at summary statistics suggests that this focus is warranted- small firms produce nearly half of private non-farm GDP and are responsible for the lion's share of employment growth over the last 10 years.

[2] https://www.occ.treas.gov/topics/community-affairs/publications/fact-sheets/fact-sheet-sba-7a-guaranteed-loan.pdf

eligible small businesses and assume all screening and monitoring responsibilities. In turn, the SBA partially guarantees the loan balance in the event of default and oversees an active secondary market for the guaranteed portion of the loan.[3] From 1990-2013, the 7(a) program approved $267.9 billion in loans through its nationwide network of lenders. Despite the length and breadth of the 7(a) program and its stated goal of relieving small business financial constraints, this paper is the first to empirically examine its effect during the financial crisis when small business financial constraints were particularly severe and therefore its benefits were potentially greatest.

The empirical analysis exploits the wide heterogeneity in the presence of SBA lenders across US counties to identify the effect of the availability of government guaranteed loans on small business loan origination, employment, and establishment growth during the recent financial crisis. Using comprehensive data from the SBA 7(a) guaranteed lending program obtained through a Freedom of Information Act (FOIA) request, I construct a measure of the local proportion of bank branches able to grant government-guaranteed loans. To preview the main results, I find that the local proportion of SBA bank branches significantly increases the amount of credit granted to small businesses during the crisis. This effect is strongest for the smallest businesses with less than $1 million in annual revenues, which is striking given that these firms are the most credit constrained in general (Beck, Demirguc-Kunt, and Maksimovic (2005), Beck, Demirguc-Kunt, Laeven, and Maksimovic (2006)), and that experience the greatest tightening of financial constraints during crises (Kroszner, Laeven, and Klingebiel (2007)). Further, I find that

[3] The use of partial government-guarantees to stimulate small business lending is not unique to the United States. Many developed countries around the globe have instituted similar programs with the aim of increasing credit availability to traditionally constrained small businesses. In that sense this study has broader implications than just for the US, although foreign credit markets may have different institutional characteristics that mitigate or enhance the effectiveness of government guaranteed lending.

the market presence of SBA lenders also corresponds to better real outcomes in terms of total employment and establishments, but again only for the smallest firms (<20 employees). Finally, I find that one-year-ahead overall unemployment also decreases. These novel results suggest a potential positive role for government guarantees in lessening the detrimental effects of banking crises on real outcomes for bank-dependent firms.

The primary identification challenge in this paper is to distinguish between a causal role for the local availability of government-guaranteed loans and the endogenous branching decisions of banks. Previous papers use the total quantity of SBA loans at the state level to identify the effect of government-guaranteed lending during the credit crunches of the 1990's and early 2000's (Hancock and Wilcox (1998), Hancock, Peek, and Wilcox (2007)). However, the amount of SBA loans granted is an equilibrium outcome resulting from the intersection of supply and demand, making causal interpretation problematic.[4] Second, the state level analysis does not reflect the local nature of small business lending. Along these lines, two initial observations motivate the use of the local proportion of SBA bank branches as the primary independent variable of interest. First, although the branch location decisions of banks are not random, they are unlikely to be driven by SBA loan opportunities in local areas. As Brown and Earle (2017) note, SBA loans constitute roughly 0.25% of the loan portfolios of the top 10 SBA lenders. Second, SBA program participation is determined at the bank, rather than the branch, level. These facts lessen concerns that SBA bank branch locations are simply correlated with local demand for SBA loans.

I conduct a battery of tests to ensure the robustness of my results and to rule out alternative channels. First, I show that the results are unlikely to be driven by correlated omitted variables related to demand. In all empirical tests I include local median income, house price growth, and

[4] These features could help to explain why the authors find a strong positive relationship between SBA lending and outcomes for large firms who are ineligible for SBA loans.

unemployment, and allow each to vary during the crisis. I find that the results are robust to the inclusion of these variables. Second, I show that SBA market presence only increases employment and establishments for the smallest firms (<20 employees) while having no impact on local large (placebo) firms. If the proportion of SBA branches is simply correlated with credit demand or local economic conditions, then all local firms should see similar patterns of credit origination and growth.

I also control for a host of local banking market characteristics to rule out alternative supply-side channels. Specifically, I include the number of large bank branches, local banking market concentration, local capital, and local bank exposure to the mortgage market, and allow these variables to vary during the crisis. These variables effectively control for channels related to the local prevalence of relationship lenders, banking market competitiveness, and bank liquidity pressures, which have been shown to effect small business lending during credit supply shocks (Cotugno, Monferrà, and Sampagnaro (2012), Jimenez, Ongena, Peydro, and Saurino (2012), Popov and Udell (2012), Iyer, Peydro, da-Rocha-Lopes, and Schoar (2013), Liberti and Sturgess (2012), Berger, Bouwman, and Kim (2016)). The results hold despite the inclusion of this wide range of local supply characteristics.

Additional tests show that the results are not driven by the definition of the crisis period, or by simultaneity bias arising from the definition of SBA market prevalence. I use the one year lag of SBA branch proportion for all tests (Berger, Cerqueiro, and Penas (2015), Berger, Bouwman, and Kim (2016)), and show that a time-invariant measure, defined as the market presence of SBA banks in the year 2003, still positively affects small business lending during the crisis.

Finally, I conduct an instrumental variables analysis to account for the bank's decision to become an SBA lender. Specifically, I predict participation in the SBA guaranteed-lending program by whether the representative of the district in which the bank is headquartered serves on U.S. House of Representatives Committee on Small Business, which has oversight over the SBA. As noted in Duchin and Sosyura (2014), membership on these committees is largely determined by House leadership, and therefore represents plausibly exogenous variation in the incentive to become an SBA lender. In addition, the use of headquarter location lessens concerns that representation also affects demand at the branch level. I then aggregate SBA participation to the county level, and use this as an instrument for the prevalence of SBA banks in a local market (similar to the approach in Berger and Roman (2015)). The IV analysis confirms the OLS results.

Ex ante, it is not clear whether the SBA guarantee would motivate lenders to *efficiently* allocate capital to financially constrained small firms during the crisis. Government intervention into private credit markets can only be beneficial in the face of frictions. Recent research suggests that at least some of the reduction in credit to small firms was indeed inefficient (Montoriol-Garriga and Wang (2012), Cole (2012), DeYoung, Gron, Torna, and Winton (2015)). Survey evidence from the National Federation of Independent Businesses supports this view, finding that only 40% of borrowers seeking credit in 2009 were able to fill their needs compared to 90% in the mid-2000s.[5] In light of this evidence, government intervention at the very least has the potential to increase efficiency.

The above description of the 7(a) program highlights how it might plausibly mitigate the major supply-side frictions exacerbated by the financial crisis: liquidity and credit risk. First, the partial guarantee lessens credit risk faced by banks while preserving the incentive to screen and monitor borrowers. Second, the provision and encouragement of an active secondary market for the guaranteed portion of the loans allows banks to easily move loans off of their balance sheet,

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[5] http://www.nfib.com/Portals/0/PDF/AllUsers/research/studies/Small-Business-Credit-In-a-Deep-Recession-February-2010-NFIB.pdf

reducing liquidity concerns. My goal in this paper is not to empirically distinguish between these two supply-side channels, only to provide a plausible explanation for the mechanism through which government guaranteed loans can be especially beneficial during crises.

On the other hand, the presence of a government guarantee may instead induce lenders to reduce screening and monitoring efforts and fund negative NPV projects (Rhyne (1988)). If the pool of potential borrowers also becomes riskier during crises as balance sheets deteriorate, then this incentive may instead reduce efficiency. Using default and charge-off data from the SBA loans, I construct tests based on the predictions of the bank moral hazard and supply frictions channels in order to see which channel empirically dominates.

I find that the proportion of SBA loans that default within 3 years, along with the proportion of the loan that is eventually charged-off, decreases during the crisis. This suggests that the average SBA borrower quality *improves*. Since the purpose of SBA loans is to provide funding to firms unable to obtain credit elsewhere, the decrease in default and charge-off rates suggests that relatively better borrowers were excluded from traditional lending markets and pushed to seek SBA loans. Taken in concert with the real outcomes results, this test provides suggestive evidence in favor of the SBA guarantee relieving the financial constraints of viable small businesses during the crisis. To my knowledge, this paper is the first to analyze outcomes for SBA loans granted during the financial crisis in order to distinguish between moral hazard and efficient capital allocation by lenders.

In the next section, I provide more detailed motivation for the analysis and its relation to extant literature. Section III describes the institutional setting of SBA 7(a) guaranteed loans. Section IV develops hypotheses. Section V explains the data and empirical approach. Section VI describes the results. Section VII details the various robustness tests. Section VIII derives potential policy implications and concludes.

II. Motivation and related literature

This paper is related to a number of strands of literature. Most generally, it contributes to the large literature concerning financial constraints and growth (see e.g. Rajan and Zingales (1998), or Levine (2005) for a useful review). Ample evidence suggests that small firms face greater financial constraints than their larger counterparts, both in the US and worldwide (see e.g., Berger and Udell (1998), Beck, Demirguc-Kunt, Maksimovic (2005), Banerjee and Duflo (2014), Zia (2008), De Mel, Mckenzie, and Woodruff (2008), Beck, Demirguc-Kunt, Laeven, and Levine (2008)). Since small firms often lack defined financial histories and audited financial statements that mitigate information asymmetry with outside investors, lenders must often instead rely on soft information about the borrower and local environment gleaned from repeated interactions (e.g., relationship lending; Petersen and Rajan (1994), Berger and Udell (1995), Berger and Udell (2002), Stein (2002)).

Additionally, this paper contributes to the literature examining the real effects of banking crises by examining a possible policy response. Opaque small firms have little to no access to public credit markets, making them dependent on bank financing and particularly prone to the deleterious effects of banking crises (Kroszner, Laeven, and Klingebiel (2007), Dell'Ariccia, Detragiache, and Rajan (2005)).

This paper is also related to the literature that examines the effect of the SBA guarantee programs on both local economic outcomes (Craig, Jackson, and Thomson (2007)) and firm outcomes (Brown and Earle (forthcoming)), and partial guarantee programs in France (LeLarge, Sraer, and Thesmar (2010)), India (Banerjee and Duflo (2014), and the UK (Cowling (2010)). My paper is distinct in its focus on the county-level proportion of government-guaranteed lenders and their differential impact during crisis times when small firms are particularly financially constrained and their potential impact is greatest. This paper is therefore similar in spirit to Hancock, Peek, and Wilcox (2007) who look at the interaction of bank size, bank capital, and SBA loans granted on local real outcomes based on firm size. However, their focus on the total amount of granted SBA loans makes causal interpretation (and therefore policy prescription) problematic since it is an equilibrium outcome, and thus the result of both local supply and demand. Contrary to this paper, they find a strong, positive relationship between the quantity of SBA loans and employment for large firms who are ineligible for SBA loans. This suggests that their empirical results may be confounded by omitted local demand characteristics.

Finally, this paper is related to the recent strand of literature looking at the effect of other types of government intervention (primarily the Troubled Asset Relief Program (TARP)) on lending. Li (2013) examines TARP recipients with low capital ratios and finds that these banks increase lending. Berger and Roman (2016) find that areas with a higher proportion of TARP banks see better real outcomes in terms of net hiring establishments and net job creation. On the other hand, Black and Hazelwood (2013) find mixed results regarding the riskiness of new loans, and Duchin and Sosyura (2014) find an increase in the riskiness of new loans and no change in credit supply in response to receiving TARP funding. Several papers also examine the effect of TARP on small business lending, also with conflicting conclusions. Puddu and Walchi (2013) find that TARP banks increase small business loan originations more than non-TARP banks. However, Cole (2012) finds that TARP banks actually reduced small business lending relative to non-TARP banks. These papers provide a thorough analysis of the effect of TARP, but reach different conclusions both for overall lending and small business lending. Importantly, I contribute to this literature by examining a different type of government intervention that directly targets small businesses.

III. Institutional setting- SBA 7(a) guaranteed loan program

a. Description

The 7(a) guaranteed lending program is the flagship program of the SBA. Through this program the SBA guarantees a substantial portion of loans granted to qualifying small businesses and delegates the screening, monitoring, and capital provision functions to participating lenders. Over my sample period of 2005-2013, the SBA guaranteed an average of $14 billion of new loans per year, which represented around 5% of total new small business loan volume.[6]

To become an SBA lender, the bank (or financial intermediary) must first apply to the SBA, "meet and maintain the ethical requirements as identified in 13 CFR Sec. 120.140", and be supervised and examined by a state or Federal regulatory authority. In addition, the specific underwriting requirements of SBA loans often come with a steep learning curve that imposes substantial initial costs on lenders. The SBA also monitors lender guaranteed loan portfolios and utilizes credit scoring technology to assign each lender a composite rating. This rating in turn determines the monitoring intensity of the SBA and is the main source for off-site reviews. Finally, each SBA lender must submit to on-site reviews at the discretion of the SBA. These costs of SBA lending help to explain why less than 5% of small business loan originations on

[6] This according to CRA originations data.

average come with an SBA guarantee, and why not all banks specializing in small business loans are SBA lenders.

The 7(a) program is specifically targeted at small businesses who have exhausted all other forms of financing. In fact, in order to qualify, the borrower must satisfy a “credit elsewhere” requirement in which she certifies that she could not obtain credit elsewhere at “reasonable terms”. The lender must in turn certify that it would not be able to provide the loan at the given terms in the absence of the SBA guarantee. The lender provides the capital for the loan and incurs all costs of screening and servicing, while the SBA guarantees up to 85% of the loan balance in the event that the borrower defaults for loans less than $150,000, and up to 75% for loans above $150,000. This partial guarantee feature is important, since the bank must retain some credit risk.

According to the SBA, the 7(a) program is generally designed to encourage longer-term small business financing. Actual loan maturity is based on borrower ability to repay and the specific type of collateral, but maximum maturities are set at 25 years for real estate, 10 years for equipment, and up to 10 years for working capital or inventory. Interest rates for SBA loans are have a fixed spread above LIBOR or the prime rate, which is capped according to initial approval amount, maturity, and fixed or variable status.[7] In practice, the interest rate cap and availability of long maturity loans make SBA loans attractive to borrowers, but these attractive contractual features are counterbalanced by high initial fees and potentially onerous application requirements. Figure I provides an example fee structure of a $1,000,000 loan.

b. SBA Summary Statistics

[7] For specific limits and requirements of the 7(a) program, see https://www.sba.gov/offices/headquarters/oca/resources/13022

Since participation in the SBA programs is non-random, it is important to assess whether the availability of government-guaranteed loans is a causal mechanism for alleviating credit constraints or whether it is simply correlated with other bank characteristics that also determined program participation. As a first pass, I calculate summary statistics for both SBA and non-SBA lenders from 2005-2013 using the population of banks from the Call Reports in Table 1.To capture bank characteristics I compute several variables: cash/total deposits (liquidity), equity/gross total assets (capital), non-performing loans/total loans (asset quality), ROA (performance), and ln(gross total assets) (size). As the table shows, SBA lenders are quite similar to their non-SBA counterparts along observable dimensions. Notably, however, non-SBA lenders have a much higher cash to deposits ratio, roughly indicating that they were more liquid during this time period.

IV. Hypotheses Development

The goal of this paper is to understand the effect of government-guaranteed lending on the supply of credit to and real outcomes of small businesses in the face of a large shock to external financing. Seminal models of financing frictions show that firms without sufficient internal capital cannot fund positive NPV projects when there is a negative shock to external finance. In the context of small business credit, these frictions primarily take the form of information frictions (Stiglitz and Weiss (1981)). In theory, the information asymmetry between lender and borrower can lead to credit rationing in equilibrium since the interest rate affects the incentives and behavior of the borrower. An increase in the interest rate causes both an increase in the average riskiness of the borrower pool (adverse selection) and the selection of riskier projects (moral hazard). In this setting, lenders set the interest rate below the market-clearing rate in order to maximize profit.

This theory directly applies to the small business credit market. A large body of empirical evidence suggests that small firms face greater financial constraints than their larger counterparts, both in the US and worldwide (see e.g., Berger and Udell (1998), Beck, Demirguc-Kunt, Maksimovic (2005), Banerjee and Duflo (2014), Zia (2008), De Mel, Mckenzie, and Woodruff (2008), Beck, Demirguc-Kunt, Laeven, and Levine (2008)). Explanations for these differential financial constraints based on firm size primarily stem from appeals to information asymmetry between small business owners and outside investors. For example, small firms often lack defined financial histories and audited financial statements that mitigate information asymmetry with outside investors. Lenders must therefore often rely on soft information about the borrower and local environment gleaned from repeated interactions (e.g., relationship lending; Petersen and Rajan (1994), Berger and Udell (1995), Berger and Udell (2002), Stein (2002)). These features not only make small business lending risky, but also renders the loans largely illiquid since soft information is by definition non-transferable.

On the supply side, two primary forces are believed to be responsible for the decrease in small business lending during the crisis. First, the crisis resulted in huge decreases in capital for many banks which, coupled with general economic uncertainty, reduced the ability and willingness of lenders to take on risk (Duchin, Ozbas, and Sensoy (2010), Ivashina and Scharfstein (2010)). Second, key sources of bank financing dried up and current borrowers drew down lines of credit, causing major liquidity concerns (Brunnermeier (2009), Gorton (2009), Ivashina and Scharfstein (2010), Cornett et al. (2011)). Since small business loans are themselves risky and illiquid, the financial crisis may have caused lenders to inefficiently reduce loans to small business by exacerbating credit risk and liquidity concerns.[8]

In the face of these large costs of small business lending which were exacerbated during the crisis, government-guaranteed lending can potentially deliver several important benefits. First, SBA loans increase the ex post return of defaulted loans, partially alleviating the higher credit risk. Second, the large and active secondary market for SBA loans allows banks to easily move the guaranteed portion off of their balance sheet, freeing up valuable capital. This *supply frictions channel* predicts that the amount of small business lending increases as a result of local SBA lender presence. Although I do not differentiate between the individual supply-side frictions in this paper, they provide an intuitive baseline for understanding how government-guaranteed lending can help to ease financial constraints in the presence of a negative shock to external financing and private market frictions.

H1: The local prevalence of SBA lenders increased the provision of small business loans during the crisis.

The prediction of an increase in local small business lending as a result of government-guaranteed lender presence does not necessarily imply that the additional loans originated were "good" loans. For example, it could also be that the presence of a government guarantee increases moral hazard by encouraging banks to reduce screening and monitoring activities. If the quality of the pool of potential borrowers also declines during economic downturns, then

[8] Aside from being more opaque, small businesses are also generally riskier than their larger counterparts. Using Census and Bureau of Labor Statistics data, Shane (2012) shows that over half of small establishments are no longer in business after 5 years, and this ratio has been increasing over time.

banks may instead reduce efficiency by making loans to more negative NPV projects on average. The *bank moral hazard* channel predicts that the presence of SBA lenders leads to worse small business outcomes on average.

H2: Greater SBA lender presence is associated with worse small business outcomes (employment, establishments, and loan default/charge-off rates) during the crisis.

In contrast, if the SBA guarantee mitigated supply-side frictions and allowed banks to extend credit to constrained-yet-viable small businesses, then small business outcomes should improve along with SBA lender presence.

H3: Greater SBA lender presence is associated with better small business outcomes during the crisis.

Of course, these hypotheses are not mutually exclusive. SBA lenders can both facilitate the loosening of financial constraints to viable small businesses during the crisis and also make loans to negative NPV projects. The goal in this paper is to see which channel empirically dominates overall.

V. Data

Data on small business loans come from the FFIEC via the Community Reinvestment Act (CRA) of 1977. This act requires that all banks over a certain asset threshold report their small business lending activities by the location of the borrower.[9] Small business lending is broadly defined as commercial and industrial loans secured by non-farm or non-residential real estate, business credit cards, and lines of credit. This broad definition captures the major sources of external financing for small firms.[10] CRA data further differentiates between small business loans smaller than $1 million and loans to small businesses with annual revenues less than $1 million. This particular feature of the data allows me to broadly distinguish between loans to all small businesses and those to only the smallest small businesses.

I obtain employment growth from the U.S Census Quarterly Workforce Indicators (QWI), which are derived from the Longitudinal Employer-Household Dynamics program. This dataset provides total employment by county and firm size, and separates employment changes into hiring and firing. The principal employment variables of interest will be the natural log of employment at the end of the second quarter (to match with bank Summary of Deposits data which is reported as of June 30th) as well as the average of quarterly hiring and separations rates.[11] These rates are directly provided by the LEHD, and have a number of nice features. First, firm size is measured at the national level, so that establishments which have a small number of employees but are part of a large firm are not counted as small businesses.[12] This feature is critical for the interpretation of the results. Second, I can distinguish whether changes in employment come from hiring or firing, where hiring is further decomposed into new hires and recall hires. Finally, firm size and age groupings provide richness to the analysis of employment changes. For the initial tests, I group all employment variables by firm size and county, where

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[9] Over my sample period, the asset threshold is $1 billion. I therefore do not capture lending by banks with fewer than $1 billion in assets. However, using Call Report data Greenstone, Mas, and Nguyen (2014) estimate that the CRA data still capture roughly 86% of all small business loan originations.

[10] The SBA Office of Advocacy reports that 42% of total financing and the majority of external financing comes from these three sources https://www.sba.gov/sites/default/files/2014_Finance_FAQ.pdf

[11] Detailed variable descriptions can be found in Table II.

[12] http://lehd.ces.census.gov/doc/QWI_101.pdf

small firms are defined as having less than 20 employees, and large firms are those with greater than 500 employees.

In addition to local employment outcomes, I also examine changes in establishment growth. Establishment data by industry and county come from the County Business Patterns database. This dataset separates the number of establishments by firm size, industry, and county. I calculate the establishment percentage growth rate first based on firm size, where size cutoffs are defined as in employment.[13] Importantly, the unit of observation in this data set is not necessarily a firm, but rather an establishment, which may be a subset of a firm. I discuss the possible implications of this feature in the empirical analysis below.

The primary explanatory variable of interest, SBA market prevalence in a local region, comes from comprehensive data on all SBA 7(a) guaranteed loans from 2005-2013.[14] To be counted as an SBA lender, a bank must have issued at least one 7(a) loan in that year in at least one of its branches. I then assign all of that bank's branches as SBA branches, regardless of whether or not that particular branch issued an SBA loan in that year. This measure relies on the assumption that all branches of an SBA lender can make SBA loans, and rather than on the endogenous matching of bank and borrower. This variable is intended to capture the relative ease by which a small business borrower could obtain a government-guaranteed loan. In this way this variable is similar in spirit to Berger, Goulding, and Rice (2014), who use the proportion of large bank branches in a region to capture the relative convenience of large banks. This measure also assumes that the matching of borrower to bank is random, and therefore the greater prevalence of local SBA branches increases the availability of government-guaranteed loans.

[13] Establishments are measured as of March.
[14] This data was obtained from a FOIA request to the SBA.

I supplement the SBA lender and local real outcome variables with county median income from the census, unemployment from the Bureau of Economic Analysis (BEA), and local house price growth from the FHFA. Since local house prices are not available at the county level, I compute local house price growth based on the weighted average of house prices of the zip codes within the county, where the weights are the proportion of county housing represented by each zip code (FHFA).

Finally, I capture local financial market characteristics using data from FDIC Call Report and Summary of Deposits data. These data allow me to observe the dispersion of bank branches across counties, and to construct detailed measures of the state of the local banking market. In the main analysis, I control for the prevalence of large bank branches, the concentration (HHI) of the county banking market, the weighted proportion of tier 1 capital, and the weighted proportion of mortgage loans in a county, which previous literature has shown to be important determinants of lending during crises (see, e.g. Berger, Cerqueiro, and Penas (2015), Berger, Bouwman, and Kim (2016)). In later robustness tests, I also include the average capital ratio of local banks to capture the potential confounding effect of bank capital on performance and lending (Berger and Bouwman (2013)), as well as measures of bank profitability (ROA), asset quality (non-performing loans/total loans), and liquidity (cash/deposits). Table 2 presents summary statistics for all variables used in the analysis.

VI. Empirical design

a. Small business credit

To examine the effect of SBA market presence on local small business credit and real outcomes during the crisis, I first construct a measure of the availability of SBA loans using comprehensive SBA loan data. SBA lenders are defined as commercial banks who have issued at least one SBA loan during the year.[15] I then mark any branch of that bank as an SBA branch, and compute the share of SBA branches over total commercial bank branches at the county level. Similar to Berger, Goulding, and Rice (2014), this measure captures the availability and convenience of branches able to grant SBA loans. The county-level measure is appropriate for my research question since most small bank borrowers are located close to bank from which they borrow.[16] Additionally, I lag the branch share of SBA banks one year to mitigate concerns of simultaneity bias.

To begin, I propose the following idealized regression to examine the effect of SBA market presence on small business credit:

$$\left(SB\ Credit\ Per\ Cap_{i,t}\right) = \alpha + \beta_1 SBA_{i,t-1} + \beta_2 Crisis + \beta_3 SBA_{i,t-1} * Crisis + \gamma_i + \epsilon_{i,t} \qquad (1)$$

The dependent variables for this analysis are the 1) number and 2) amount of small business loans and 3) number and 4) amount of loans to small businesses with annual revenues less than \$1 million at the county level divided by county population. Small business loans are broadly defined by the CRA as commercial and industrial loans secured by non-farm or non-residential real estate, lines of credit, and business credit cards, with initial amounts less than \$1 million.[17]

i. Description of key independent variable

[15] My data does not identify the particular branch that grants an SBA loan, only the bank itself.
[16] Petersen and Rajan (2002) find that small business borrowers are located a median of 9 miles from their bank branch.
[17] During the sample period, only commercial banks with total asset > \$1 billion had to report this data, but many small banks also reported. This data represents the most comprehensive small business lending data in the US.

The key independent variable, the ratio of SBA branches to total bank branches in a county, is meant to capture the relative convenience of SBA lenders both in normal times and during the crisis. [18] The construction of this variable as a ratio follows recent literature examining the effect of various local financial market characteristics on small business lending (see e.g., Berger, Goulding, and Rice (2014), Berger, Cerqueiro, and Penas (2015), and Berger, Bouwman, and Kim (2016)). The analysis therefore assumes several features of the process by which small business borrowers match to lenders. First, it assumes that borrowers search for loans randomly across lenders, and therefore that a higher proportion of SBA lenders therefore leads to a higher probability of receiving an SBA loan. Without detailed data on this search process, this represents the most agnostic approach. Second, it assumes that the relevant market for small business credit is the county, which is appropriate given the local nature of small business lending (Petersen and Rajan (2002)).[19]

This measure has a number distinct advantages over the total quantity of SBA loans at the state level, which has been used in extant studies of SBA lending during credit crunches (Hancock and Wilcox (1998), Hancock, Peek, and Wilcox (2007)). First, it better captures the reality of the local nature of small business lending. Second it is less likely to be confounded by local demand for SBA loans. Brown and Earle (2017) estimate that SBA loans make up only around 0.25% of the loan portfolio of the top 10 SBA lenders. Coupled with the fact that the decision to become an SBA lender is made at the bank (rather than the branch) level, this mitigates concerns the proportion of local SBA branches simply reflects a higher demand for SBA loans.

[18] I utilize the dummy variable *Crisis* in place of a full set of year fixed-effects as in Berger, Cerqueiro, and Penas (2015) to facilitate the interpretation of the results.
[19] As a robustness check, I instead substitute the natural log of the number of SBA branches in a county and control for the number of local banks and find similar results. Results available upon request.

ii. Local economic conditions and credit demand

The first-pass, idealized regression potentially suffers from omitted variable bias and thus does little to argue for a causal effect of SBA market presence on small business loans. The primary identification challenge in this paper is distinguishing small business credit supply from demand. Despite the relative unimportance of SBA loans in a lenders portfolio, the prevalence of SBA lenders in a county may be correlated with factors related to credit demand, in which case the interpretation of β_3 is unclear. Table 3 shows that there are some differences between counties with a high proportion of SBA lenders ("treated") and those with a low proportion ("control"). Most notably, high SBA counties (defined as those with above median proportion of SBA branches over the sample period) tend to have slightly higher income and unemployment, along with higher house price growth. Despite these differences, it is ex ante unclear how these characteristics should affect the results. On the one hand, higher income areas could be better able to weather the crisis. On the other hand, high unemployment areas may have fewer investment opportunities, especially during the crisis.

Therefore, to mitigate concerns of correlated omitted demand factors, I add three controls to the main specification: the natural log of county median income, county unemployment rate, and local house price growth. These variables reasonably capture local economic conditions related to credit demand and have been used extensively in recent literature (see e.g., Adelino, Schoar, and Severino (2015), Adelino, Ma, and Robinson (forthcoming), Berger, Cerqueiro, and Penas (2015), Berger, Bouwman, and Kim (forthcoming)). However, it is also possible that credit demand and economic conditions vary in crisis times in a manner that is correlated with the prevalence of SBA lenders. For example, SBA lenders may tend to locate in high income areas that were better able to weather the crisis (i.e. higher demand during the crisis). Therefore, to control for this potential confounding effect, I also allow each of the local economic variables to vary between normal and crisis times.

Table 4 reports the results from this specification. The coefficient on the interaction of SBA suggests that a one standard deviation increase in the proportion of SBA lenders increases per capita credit volume to the smallest firms (those with less than $1 million in annual revenues) by roughly 8.2%. The results of columns 1-4 consistently show that this alternative demand story is unlikely to explain the results, and that the increase in small business lending associated with the presence of SBA is potentially independent of credit demand concerns.

iii. Local financial market characteristics

In addition to controlling for local demand-side characteristics, it is also important to determine whether the proportion of SBA lenders in a local area is indeed the relevant supply-side characteristic to examine. If SBA lending during the crisis is correlated with some other local financial market characteristic, then the mechanism through which credit is supplied could be spuriously attributed to government-backed lending. It is therefore important to control for significant supply-side characteristics of local markets in order to identify the causal channel. Recent literature examining the effect of local financial market characteristics on small business lending during the crisis provides some guidance in this respect. Chief among the studied characteristics is the market share of small banks (Berger, Cerqueiro, and Penas (2015), Berger, Bouwman, and Kim (forthcoming)) or, more generally, the presence of relationship lenders (Cotugno, Monferra, and Sampagnaro (2012), Jimenez, Ongena, Peydro, and Saurino (2012), Popov and Udell (2012), Iyer, Peydro, da-Rocha-Lopes, and Schoar (2013), Liberti and Sturgess

(2012)). If SBA lenders are simply small or relationship lenders, then the impact of government-backed lending will be indistinguishable from the impact of relationship lending.

However, the SBA loan data show that this particular market characteristic is unlikely to affect the results. Specifically, small banks are typically associated with relationship lending due to the relative ease by which they can process relevant soft information (Petersen and Rajan (1994, 2002), Berger and Udell (1995, 2002)). However, small banks provide only 24% of all SBA loans over the sample period and 34% of the volume. I nevertheless control for this characteristic by including the natural log of the number of large bank branches in a county, where a large bank is defined as having at least $1 billion in total assets.[20] In addition to the number of large bank branches, I also control for the competitiveness of the local market using the HHI of county branch deposits, for the capital positions of local banks using the weighted average tier 1 capital ratio, and for local bank exposure to the mortgage market using the weighted average mortgage loan ratio (Berger, Cerqueiro, and Penas (2015)).[21] Finally, similar to above, I allow each of these variables to vary in crisis times.

The main specification used in all subsequent analysis incorporates both the supply and demand variables described above:

[20] Results are robust to alternative definitions, such as median bank size (in assets), or proportion of large bank (>$5 billion in GTA) branches in the county.
[21] Deposits are the only variable available at the branch level. Therefore, the weights are determined using local market deposit share.

$$\begin{aligned}(SB\ Credit\ Per\ Cap._{i,t}) \\ &= \alpha + \beta_1 SBA_{i,t-1} + \beta_2 Crisis + \beta_3 SBA_{i,t-1} * Crisis \\ &+ \beta_4 Local\ Market\ Chars._{i,t} + \beta_5 Local\ Market\ Chars._{i,t} * Crisis \\ &+ \beta_6 Local\ Bank\ Chars._{i,t} + \beta_7 Local\ Bank\ Chars._{i,t} * Crisis + \gamma_i + \epsilon_{i,t}\end{aligned} \tag{2}$$

Table 5 reports the results of this analysis including both local demand and supply characteristics. Importantly, the inclusion of supply-side variables shown to be important in previous literature does not affect the results.

iv. SBA vs. Non-SBA loans

The analysis regarding total local small business credit in local regions is appropriate given the policy focus on this outcome. However, it is also important to distinguish whether the increase in small business credit is coming from SBA loans or traditional loans. Separating the two types of loans helps to pin down whether lenders that choose to participate in the 7(a) program are simply better at small business lending in general, or whether the SBA guarantee actually has a differential impact.

To match the SBA loan data to the CRA data, I first remove all banks with less than $1 billion in total assets. Since the SBA loan data does not include firm revenues, I focus on SBA loans with initial amounts less than $100,000 to align with the stronger finding of an increase in credit for small (<$1 million in annual revenue firms). I aggregate these small SBA loans by county and year, then match to the corresponding bucket in the CRA data. Since the SBA loans are a subset of the CRA, I can then compute the total number of traditional small business loans.

I then scale this variable by population, and estimate the model outlined in Equation 2. The results of this analysis are reported in Table 6.

I find that only SBA loans per capita increase during the crisis with the local proportion of SBA lenders, while traditional loans are not affected.[22] This finding mitigates concerns that SBA lenders simply specialize in small business lending, and thus that the government guarantee has no independent effect on credit provision.

b. Local real outcomes

The finding of an increase in small business credit during the crisis when access to a government guarantee is greater, while interesting and important given the substantial decline in small business lending during this same time period, is perhaps unsurprising. When lenders have partial insurance provided by the government, it is natural that they will extend more loans. Yet it is also possible that the bank will expend less effort in screening and monitoring small business borrowers, and thus inefficiently allocate capital to poor quality borrowers. Therefore, it is important to analyze not only whether credit increases, but also whether this increase in credit leads to better real outcomes, both for small firms and the local economy as a whole. In this section I tackle this question by examining the effect of SBA market prevalence on real outcomes for small firms and the local economy. Although the data do not allow me to view the borrowers themselves, the preeminent role of commercial bank loans for the external financing of small firms in general provide an intuitive tie to the small business credit results.[23]

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[22] It is important to note that the coefficient on non-SBA loans is still positive, yet insignificant. It is possible that general equilibrium effects of government intervention, whereby an increase in government-guaranteed lending spurs the local economy and subsequently drives up traditional lending, are also coming into play here.
[23] As noted above, commercial banks are the primary source of external funding for small businesses (Cole, Wolken, and Woodburn (1996)).

The results of this analysis have important policy implications. If government-guaranteed lending encourages inefficient allocation of capital by muting screening and monitoring incentives at banks, then the SBA 7(a) program simply represents a wealth transfer. If instead this program alleviates small business financial constraints in the face of private market frictions, then policymakers can potentially improve capital allocation and spur economic growth through their intervention.

i. Future Unemployment

I begin my analysis of local real outcomes by examining the effect of SBA market prevalence during the financial crisis on one-year ahead county unemployment. For this analysis, I include the full set of local supply and demand controls, along with their interactions with the crisis dummy. If the presence of SBA lenders decreases future unemployment, then this suggests that small firms that received credit in these regions were indeed financially constrained, and access to government-backed loans allowed them to expand employment, at least in the short term.

Table 7 presents the results of this analysis. The results show that the presence of SBA lenders in a local market during the crisis significantly decreases future unemployment. One-year ahead county unemployment is measured here in percentage terms, so the coefficient on the interaction of SBA lender presence and the crisis indicates that a one-standard deviation increase leads to a 3.2% decrease in future unemployment. Although small, this effect is surprising given that the overall ratio of SBA loans to other small business loans is less than 5%. Furthermore, this result provides suggestive evidence that lenders are not using the government guarantee in order to fund negative NPV projects.

ii. Employment- small vs. large firms

I next examine the differential impact of SBA market prevalence on employment for small and large firms. This analysis not only allows me to explore what types of employment drive the decrease in future unemployment, but also allows me to rule out confounding demand explanations for my results, and strengthen identification. If the presence of SBA lenders is correlated with local economic characteristics that allow certain areas to better weather the crisis and are not captured by the controls, then both large firms and small firms should see better outcomes during the crisis. On the other hand, if the improvement in real outcomes is concentrated only in small firms, then this supports the supply-side, causal interpretation of the effect of SBA market presence. In this way I can use local outcomes for large firms as a sort of placebo test.

The results of Table 8 show that the latter, supply-side interpretation is more appropriate. The dependent variable in columns 1 and 2 is the natural log of employment (Adelino, Song, and Ma (2016)). These columns show that small firms (< 20 employees) in areas with a higher proportion of SBA lenders increase employment on net during the crisis, while large firm (> 500 employees) employment remains unaffected. A one standard deviation increase in the proportion of SBA lenders increases the net job growth rate for the smallest firms by 0.6%.

Table 9 explores whether this increase in net employment is driven by an increase in hiring or a decrease in firing. The results suggest that SBA market presence affects net employment primarily by allowing small firms to hire more, rather than by allowing them to refrain from firing employees. This result is important because it supports the notion that small firms faced greater financial constraints during the crisis which restricted their growth, and that access to capital in the form of SBA lenders allowed them to expand.

iii. Establishments- small vs. large firms

I next look at the change in establishment growth for large and small firms. For this analysis, I calculate the percent growth rate in the number of establishments at the county level, and examine the differential impact of SBA lender presence during the financial crisis.

Table 10 shows that small firm establishment growth increased when small business borrowers had greater access to SBA lenders, while large firm establishment growth remained unchanged. This effect is not only statistically significant, but also highly economically significant. A one-standard deviation increase in the proportion of SBA lenders increases the small firm establishment growth rate by 0.004. This effect is huge relative to the sample mean small establishment growth rate of -0.0029, and suggests that the availability of government-backed small business lending allows potential entrepreneurs to start new firms.[24]

c. SBA default rates and charge off

Detailed data on SBA loan outcomes allows me to address some of the concerns about the quality of SBA loans made during the crisis. Although I do not see small business investment, I do observe whether the loans are charged off, and the total amount charged to the SBA. These

[24] These establishment results come with a caveat. Establishments are measured as a subset of firms. Therefore, it is impossible in this data to disentangle small firms from the small establishment subsidiaries of large firms. However, taken in conjunction with the above employment data for which this caveat does not exist, it is reasonable to assume that the majority of the growth in the number of small establishments is in fact driven by small firms rather than their larger counterparts. This then implies that at least part of the increase in net employment comes from new small firms, which are important drivers of economic growth (see e.g., Decker, Haltiwanger, Jarmin, and Miranda (2014), Adelino, Ma, and Robinson (2016)). In unreported analysis, I conduct analysis on net employment growth based on firm age. I find that the increase in employment is concentrated not in new firms, but rather in those from 2-3 years of age. Results available upon request.

measures allow me to construct rough measures of the average quality of loans granted during the crisis, and provide suggestive evidence on whether or not banks funded negative NPV projects in response to the dulled screening and monitoring incentives of SBA lending. These results add an important element to any policy debate surrounding SBA loans.

This analysis may also provide indirect evidence of credit rationing. Since SBA borrowers must, by definition, be unable to receive bank credit at reasonable terms via a traditional loan, the crisis may have pushed more borrowers who would otherwise be able to receive a traditional small business loan into SBA loan programs. Therefore, if the default rate and charge off amount of loans granted during the crisis decrease, then this suggests that better borrowers were indeed rationed from the private credit market during the crisis and forced into SBA loans.

Table 11 reports the results of this analysis. In column 1, I first compute the 3-year default rate of SBA loans granted. I then regress this rate on the crisis dummy and the controls for local demand and their interactions with the crisis dummy. Interestingly, the default rate of SBA loans granted during the crisis decreases by 50 basis points, suggesting that the borrowers receiving SBA loans during this period were better quality on average. Although the default rate decreases during the crisis, the amount charged off remains unchanged (column 2). In columns 3 and 4, I include the controls for local credit supply, including the prevalence of SBA lenders. Interestingly, when the proportion of SBA lenders is greater, the default rate decreases even more as does the percent of loans charged off, potentially suggesting a greater information advantage of local lenders.[25] Taken with the results on real outcomes for small firms, these results are consistent with the interpretation that SBA loans granted during the crisis funded

[25] This interpretation is consistent with DeYoung, Glennon, and Nigro (2008), who find that the physical distance between borrower and lender is positively related to loan default.

positive NPV projects and helped to mitigate financial constraints for small firms cut off from traditional loans.

VII. Robustness

a. Instrumental Variables

Despite extensive controls and subsample analysis, the endogeneity of SBA lending program participation may bias the results. For example, banks that specialize in small business lending may also be more likely to participate in the SBA. This could generate the positive empirical relationship between SBA lender presence and local small business outcomes given that these banks would be more likely in general to issue small business loans.

Therefore, in this section I conduct a 3-stage instrumental variables analysis as described in Wooldridge (2002) section 18.4.1 and similar to that conducted in Berger and Roman (2016) to nail down the causal effect of SBA lender presence. For this procedure, I first conduct a bank-level probit regression predicting participation in SBA lending programs controlling for bank characteristics and including two instruments. Extant literature finds a positive relationship between political connections and the probability of receiving TARP funds (Duchin and Sosyura (2012), Li (2013), Berger and Roman (2016)). More broadly, these papers show that local representation on specific Congressional committees (in the above cases, the Subcommittess on Financial Institutions or Capital Markets) directly impacts participation in government programs.

In a similar vein, I propose that the presence of a local representative on the House Committee on Small Business, which has oversight over the SBA, affects the willingness and ease with which banks can participate in SBA programs. The instruments I use in the regression are a dummy variable for whether the bank headquarters resides in a county in which the local representative sits on the House Committee on Small Business, which has oversight over the SBA, and whether this representative is a Democrat.[26] Anecdotal and empirical evidence suggests that is important to not only account for overall representation on the committee, but also for the party affiliation of that representation (Li (2013)). In general, Democrats are largely supportive of SBA programs while Republicans are not.[27, 28] Both instruments are measured as of year *t-1*. These instruments are similar to those used in Duchin and Sosyura (2014) and Berger and Roman (2016), who use representative membership on the House Subcommittee on Financial Institutions or Capital Markets as an instrument for receiving TARP funds. As these papers explain, membership on these committees is determined by House leadership, and thus represents plausibly quasi-exogenous variation in the incentives to become SBA lenders.

I also include in this regression multiple bank-level controls, such as proxies for bank profitability (ROA/Gross Total Assets), liquidity (Cash/Total Deposits), asset quality (Non-performing Loans/Total Loans), capital (Total Equity/Gross Total Assets), and bank size (Ln(Gross Total Assets), along with year fixed effects to control for yearly trends in SBA participation.

The results in Table 12 Panel A show that the instruments clearly satisfy the relevance restriction. However, there may be some concern that representation on the House Committee on Small Business is related to local small business credit and outcomes through other channels

[26] The mapping of congressional districts to counties comes from https://www.census.gov/geo/maps-data/data/cd_state.html

[27] https://clarke.house.gov/issues/small-business is one example of the Democratic approach to the SBA from a member of the committee.

[28] Republican politicians have historically sought to dismantle or reduce funding for the SBA beginning with Ronald Reagan, who tried to combine it with the Department of Commerce, and continuing with George W. Bush, who oversaw large staffing and budget cuts http://www.marketwired.com/press-release/democratic-loss-on-november-7-could-kill-small-business-administration-says-american-707941.htm .

besides SBA programs, and thus that the exclusion restriction is violated. For example, representatives are likely to undertake initiatives to benefit their own constituent small businesses, and thus may be able to influence local small business outcomes directly. The use of bank *headquarter* location to determine representation on the House Small Business Committee mitigates much of this concern. That is, although representatives would be concerned with the small business outcomes in the area where the headquarters is located, they would not necessarily be concerned with those in the branch locations. Since the majority (76%) of SBA loans are granted by larger banks who are more geographically dispersed, this particular concern is therefore unlikely to violate the exclusion restriction.

In the second step, I take the predicted value for SBA participation from the bank level regression and aggregate it to the county level, weighting by the proportion of branches, and use this as the instrument for SBA branch share.[29]

Table 12 reports the results of the analysis. Panel A shows the first-stage bank probit regression including lagged committee representation and lagged Democratic committee representation as instruments. Consistent with the notion that Democrats encourage SBA programs, Democratic representation on the House Committee on Small Business increases the probability of being an SBA lender for banks within the district. Interestingly, once controlling for Democratic representation, overall representation negatively predicts SBA participation.

Panel B shows the final stage results after using the aggregated predicted SBA participation as an instrument. Importantly, the first-stage F-test suggests that the instrument is valid. As the table shows, the principle results for small business credit volume to the smallest firms and small firm employment remain robust to this procedure. Taken together with the extensive set of

[29] This approach differs from the "forbidden regression" in that obtained variables from the first-stage probit are used as instruments and not regressors, which allows for improved efficiency (Wooldridge (2002)).

controls and subsample analysis, this test lends further credence to the causal role of SBA lender presence during the crisis.

b. Additional local bank variables

In addition to the availability of large bank branches, local banking competition, weighted average tier 1 capital ratio, and weighted average mortgage loan ratio, other banking variables could potentially could potentially play an important role in lending. For example, general bank capital (e.g., Peek and Rosengren (1995), Boot and Thakor (2000), Berger and Bouwman (2013)), bank liquidity (Berger and Bouwman (2009)), bank profitability, and bank asset quality could also plausibly affect lending during the crisis. To ensure that these local financial market characteristics are not driving the results, I follow Berger and Roman (2016) and compute the average local capital position as the sum of each local bank's equity over gross total assets, cash over total deposits, annualized ROA, and non-performing loans over total loans, each multiplied by the bank's proportion of local deposits.[30] Similar to large bank offices and HHI, I also allow these measures to vary during the crisis.

The results of Table 13 show that the inclusion of these important local banking characteristics does not change the main results, both in terms of small business credit volume and local real outcomes.

c. Time-invariant measure

There may still be some concern of endogeneity related to the location of SBA branches. So, as an alternative definition to the contemporaneous measure of SBA bank prevalence, I calculate

[30] These variables represent proxies for some of the CAMELS variables as in Duchin and Sosyura (2014).

the percent of SBA bank branches in a county in the year 2003, and use this as the primary explanatory variable of interest. After controlling for a wide range of local economic conditions and local market characteristics, it is unlikely that the locations of branches 5 years prior to the crisis are related to contemporaneous credit demand during the crisis.

Table 14 shows the results with this new measure. Since this measure of access to government-guaranteed loans is time-invariant, county fixed effects are dropped from the specification.[31] The results remain robust to substituting a predefined measure of SBA market presence, suggesting that reverse causality is not a major concern in the main specification.

d. Predicted SBA Branch Share

I next test whether the financial crisis affected participation in the SBA guaranteed-lending programs. This test is important since it can rule out concerns of endogeneity resulting from reverse-causality. For example, if the financial crisis encouraged banks to become SBA lenders to alleviate credit risk and increase liquidity, then I may find biased results. Therefore, I test whether the financial crisis increased the prevalence of SBA lenders by regressing year-ahead SBA branch share on the complete set of controls. Importantly, I also control for contemporaneous SBA branch share since there is a strong degree of stickiness in the branch share measure.

The results of Table 15 show that the financial crisis dummy is unrelated to year ahead SBA branch share. This test helps to mitigate concerns of bias arising from reverse-causality.

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[31] For this reason and due to the robustness of the results to this alternative measure, I prefer the time-varying measure of SBA market prevalence.

e. Alternative definition of crisis

Due to the definition of banking variables as of Jun. 30, the crisis dummy captures the period Jul. 1, 2007 – Jun. 30, 2009. This measure potentially leaves off a significant share of the financial crisis, particularly at the end. To ensure that the results are not driven by this choice of crisis definition, I construct an alternative proxy that also includes the end of 2009. By necessity, this variable also includes the first six months of 2010, which is technically post-crisis. Therefore, this definition biases against finding any effect since it mixes in post-crisis outcomes.

Table 16 shows that substituting this alternative definition of the crisis does not change the main results.

VIII. Policy implications and conclusion

In this paper I examine the effect of a large and long-running partial-guarantee loan program on small business lending during the recent financial crisis. In the absence of frictions in the private small business credit market, government intervention simply represents an inefficient transfer. However, theory and empirical evidence suggests that such frictions, usually arising from information asymmetry, do exist, and thus point to a potential beneficial role of government intervention. In addition, bank liquidity and credit risk concerns increased during the financial crisis which further tightened financial constraints for small firms, underscoring the importance of evaluating this program during crisis times when it potentially has the most benefit.

I find that the local prevalence of lenders able to grant government-guaranteed loans significantly increased small business credit during the recent financial crisis when small firms were particularly financially constrained. Consistent with financial constraints hindering investment, I find that small firms then expanded in terms of both employment and establishments. I also find that the crisis is not associated with an increase in the default rate of SBA loans or in the amount eventually charged to the SBA. This suggests that SBA loans were not made to worse borrowers on average, but instead to small firms facing greater financial constraints who were unable to receive traditional loans during the crisis. Finally, although I do not observe investment by small businesses, I do find that one-year ahead unemployment decreases in counties with a higher proportion of SBA lenders, indicating that small firm employment plays an important role in local unemployment as a whole and mitigating concerns that SBA loans are used to fund negative NPV projects.

The findings of this paper have important policy implications. Importantly, these results do not capture the potential aggregate effect of the SBA guarantee. For example, the program can have both positive and negative spillover effects that are beyond the scope of this analysis. And although I can see rough measures of loan and real outcomes, I cannot see the overall cost of the program. Therefore, the results should be interpreted with caution, and viewed chiefly as benefits to consider in policy discussion. Whether these same benefits can be achieved at lower cost to the taxpayer is beyond the scope of this paper, but an important question for future research.

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Figure 1
Example fee structure on $1,000,000 SBA 7(a) loan. Provided by http://www.cfa-commercial.com/sba-loan-rates-fees-and-closing-costs/

$26,250 – 3.5% SBA guarantee fee (the percentage ranges based on the size of the loan amount) The guarantee fee is calculate off of the portion of the loan amount which is actually guaranteed by the SBA. This is normally set at 75% of the total loan amount on a SBA 7a loan (75% x $1,000,000 = $750,000 x 3.5% = $26,250). This fee is financed into the loan amount.
$4,000 Appraisal Report (some areas of the country maybe lower than this, but not by much. If your buying a business, with no real estate, the appraisal will likely be lower at appr $2,000.)
$1,800 Phase One Environmental Report
$1,500 Title (Title cost vary considerably depending on the state and loan amount)
$2,500 SBA Packaging Fee (This is an optional expense that most banks charge the borrower)
$2,500 Attorney Review Fee (This is another optional fee, that funding sources charge to borrowers)
Total: $38,550

Table 1- Summary Stats for SBA and non-SBA banks

Selected bank characteristics loosely based on CAMELS proxies (defined in Table II) for SBA and non-SBA lenders for the time period 2004-2013.

Variable	Obs (Bank Year)	Mean	Std. Dev	Min	Max
SBA Lenders					
Cash/Deposits	16,686	0.13	4.67	0.00	444.04
Equity/Gross Total Assets	12,848	0.10	0.05	0.01	0.94
Non-Performing Loans/Total Loans	16,681	0.01	0.02	0.00	0.31
ROA	16,654	0.00	0.02	-0.41	0.17
Ln(Gross Total Assets)	16,809	12.64	1.40	8.77	21.09
Non-SBA Lenders					
Cash/Deposits	49,030	0.483	21.295	0.000	2457.066
Equity/Gross Total Assets	39,335	0.118	0.083	-0.004	1.000
Non-Performing Loans/Total Loans	48,723	0.013	0.028	0.000	1.000
ROA	48,818	0.004	0.039	-0.916	3.532
Ln(Gross Total Assets)	49,979	11.767	1.258	4.522	20.400

Table 2- Summary statistics and descriptions of variables used in the analysis

Variable	Definition	Source	Mean	S.D.
Small Business Credit				
Volume of SB loans per capita	Total volume of all business credit cards, lines of credit, and C&I loans secured by non-farm or non-residential real estate with initial amounts < $1 mil. divided by county population	FFIEC (CRA)	0.563	0.405
Number of SB loans per capita	Number of total number of all business credit cards, lines of credit, and C&I loans secured by non-farm or non-residential real estate with initial amounts < $1 mil. divided by county population	FFIEC (CRA)	0.018	0.012
Volume to < $1 Mil. per capita	Total volume of all business credit cards, lines of credit, and C&I loans secured by non-farm or non-residential real estate to firms with < $1 mil. in total annual revenue divided by county population	FFIEC (CRA)	0.265	0.214
Number to < $1 Mil. per capita	Natural log of total volume of all business credit cards, lines of credit, and C&I loans secured by non-farm or non-residential real estate to firms with < $1 mil. in total annual revenue divided by county population	FFIEC (CRA)	0.008	0.005
Real Outcomes				
Ln(Employment)	Natural log of quarter-end employment by county	LEHD	9.175	1.524
All Hiring Rate	Annual average of quarterly (All hires/Average Employment) measured end of June	LEHD	0.142	0.0337
New Hiring Rate	Annual average of quarterly (New hires/Average Employment) measured end of June	LEHD	0.0898	0.0272

Separations Rate	Annual average of quarterly (Separations/Average Employment) measured end of June	LEHD	0.136	0.0300
% Change in Establishments	Annual % change in the number of establishments	County Business Patterns	-0.00272	0.0360
Local Market Characteristics				
Ln(Median Income)	Natural log of county median income	Census	10.66	0.234
Weighted HPI Growth	Growth in zip-level all transaction house price index, weighted by % of county residential housing residing within each zip code	FHFA	0.00737	0.0566
Unemployment Rate	County unemployment rate	BEA	7.064	2.950
Financial Market Variables				
SBA Branch Share	% of county bank branches owned by banks that issued at least one SBA loan	SBA Loan Data, SOD	0.498	0.273
Ln(# Large Bank Branches)	Natural log of number of branches of banks with at least $1 billion in total assets	Call Report, SOD	2.306	1.319
Median Bank Size	Median size (in assets) of banks operating within a county	Call Report, SOD	1.350e+07	6.260e+07
HHI	Concentration of deposits in county	SOD	0.108	0.158
Tier 1 Capital Ratio	Ratio of tier 1 capital to gross total assets of local (county) banks	Call Report, SOD	0.101	0.052
Mortgage Loan Ratio	Ratio of mortgage loans to total loans of local (county) banks	Call Report, SOD	0.651	0.117

Non-Performing Loans Ratio	Weighted proportion of each local bank's NPL/total loans	Call Report, SOD	0.012	0.016
Bank Liquidity	Weighted proportion of each local bank's cash/total deposits	Call Report, SOD	0.066	0.034
Bank Profitability	Weighted proportion of each local bank's annualized net income/gross total assets	Call Report, SOD	0.006	0.009
Average Equity Ratio	County-year sum of (each local bank's equity/gross total assets) multiplied by the bank's proportion of local bank deposits	Call Report, SOD	0.0661	0.0484
% Large Bank Offices	% of county bank branches owned by banks with at least $5 billion in gross total assets	Call Report, SOD	0.208	0.249

Table 3- Summary Statistics by County, Year, and SBA Presence

The table displays summary statistics by county and year (2005-2013). *High SBA* refers to counties with a higher proportion of SBA lenders than the median over the whole sample period, and *Low SBA* is below median.

	High SBA		Low SBA	
Variable	Obs	Mean	Obs	Mean
Median Income	12,863	45,395	14,958	40,479
Unemployment Rate	12,937	7.14	14,944	6.84
Population	13,085	151,872	15,153	50,788
(Branches*1000)/Pop.	13,594	0.42	15,184	0.52
HHI	13,594	0.11	15,184	0.16
Mortgage Ratio	13,590	0.64	15,182	0.63
Tier 1 Capital	13,029	0.08	15,145	0.12

Table 4- Controlling for local demand conditions

The table displays coefficients from panel regression models of the total volume (column 1) and total number (column 2) of small business loans with initial amount less than $1 million per capita, and the volume (column 3) and number (column 4) of small business loans to firms with less than $1 million in annual revenues per capita. The models also include the natural log of county median income, county unemployment rate, and local house price growth and the interactions of these variables with the crisis dummy. Standard errors are clustered at the county level.

	(1)	(2)	(3)	(4)
	Loans<$1 Mil.		*Firms<$1 Mil. Rev.*	
VARIABLES	Volume per capita	Number per capita	Volume per capita	Number per capita
SBA Branch Share (t-1)	0.02	-0.06***	0.01	0.01
	(0.794)	(-3.498)	(0.335)	(0.778)
Crisis	-1.36***	-2.23***	-3.00***	-1.92***
	(-4.811)	(-10.937)	(-7.667)	(-6.919)
SBA Branch Share (t-1) * Crisis	0.00	-0.01	0.08**	0.04*
	(0.089)	(-0.750)	(2.330)	(1.767)
Ln(Median Inc.)	-0.75***	-1.81***	-1.52***	-1.97***
	(-10.939)	(-37.358)	(-19.121)	(-36.455)
Ln(Median Inc.) * Crisis	0.13***	0.20***	0.26***	0.16***
	(4.890)	(10.842)	(7.344)	(6.069)
Ln(Population)	0.61***	0.33***	0.55***	0.74***
	(4.860)	(3.139)	(3.778)	(6.367)
Weighted HPI Growth	-0.04	-0.67***	0.10	-0.11*
	(-0.665)	(-9.869)	(1.195)	(-1.668)
Weighted HPI Growth * Crisis	0.12	1.18***	0.32*	1.01***
	(0.920)	(10.920)	(1.960)	(8.173)
Unem. Rate	-0.10***	-0.19***	-0.12***	-0.17***
	(-46.360)	(-86.849)	(-42.595)	(-74.422)
Unem. Rate * Crisis	0.01***	0.03***	0.03***	0.03***
	(4.353)	(11.942)	(8.443)	(11.215)
Constant	12.00***	23.51***	20.16***	19.91***
	(9.158)	(22.267)	(13.141)	(17.070)
Observations	24,229	24,229	24,229	24,229
R-squared	0.789	0.268	0.310	0.683
Number of Counties	2,741	2,741	2,741	2,741
County FE	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5- Controlling for local financial market characteristics
The table displays coefficients from panel regression models of the total volume (column 1) and total number (column 2) of small business loans with initial amount less than $1 million per capita, and the volume (column 3) and number (column 4) of small business loans to firms with less than $1 million in annual revenues per capita. The estimated models include all variables from Table 4 along with the natural log of the number of large bank branches, the HHI of deposits, the weighted average ratio of mortgage loans, and the weighted average of Tier 1 capital ratios in the county. Standard errors are clustered at the county level.

	(1)	(2)	(3)	(4)
	Loans<$1 Mil.		*Firms<$1 Mil. Rev.*	
VARIABLES	Volume per capita	Number per capita	Volume per capita	Number per capita
SBA Branch Share (t-1)	-0.059***	-0.004***	-0.036***	-0.001***
	(-5.068)	(-9.453)	(-5.584)	(-5.633)
Crisis	-0.662***	-0.021***	-0.435***	0.001
	(-4.156)	(-4.558)	(-4.683)	(0.608)
SBA Branch Share (t-1) * Crisis	0.020*	0.001***	0.034***	0.001***
	(1.848)	(4.190)	(4.795)	(5.565)
Ln(# Large Bank Branches)	-0.003	-0.003***	0.002	-0.001***
	(-0.621)	(-15.106)	(0.523)	(-14.396)
Ln(# Large Bank Branches * Crisis)	-0.006*	0.001***	-0.009***	-0.000
	(-1.866)	(5.115)	(-5.038)	(-0.450)
HHI	-0.012	0.006***	0.030	0.003***
	(-0.445)	(5.605)	(1.514)	(5.598)
HHI * Crisis	-0.041*	-0.003***	-0.054***	-0.002***
	(-1.818)	(-2.723)	(-3.647)	(-4.829)
Tier 1 Capital Ratio	-0.713***	-0.040***	-0.531***	-0.014***
	(-6.761)	(-9.876)	(-6.534)	(-8.567)
Tier 1 Capital Ratio * Crisis	-0.102	-0.002	-0.024	0.001
	(-1.168)	(-0.789)	(-0.415)	(0.641)
Mortgage Ratio	-0.039	-0.005***	-0.004	-0.001**
	(-0.993)	(-3.207)	(-0.130)	(-2.020)
Mortgage Ratio * Crisis	0.073***	0.001	0.022	-0.000
	(3.091)	(1.304)	(1.477)	(-0.851)
Constant	2.379***	0.117***	2.585***	0.083***
	(5.496)	(8.524)	(10.946)	(14.796)
Observations	23,052	23,052	23,052	23,052
R-squared	0.339	0.190	0.316	0.133
Number of Counties	2,730	2,730	2,730	2,730
County FE	Yes	Yes	Yes	Yes
Local Econ Vars.	Yes	Yes		

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6- SBA vs. non-SBA loans

The table displays coefficients from panel regression models of the total volume on non-SBA (column 1) and SBA (column 2) loans with initial amount less than $100,000 per capita, and the percentage of SBA loans under $100,000 (column 3). The estimated models include all variables from Table 5. Standard errors are clustered at the county level.

VARIABLES	(1) Non-SBA Volume per capita	(2) SBA Volume per capita	(3) SBA Volume/Total Volume
SBA Branch Share (t-1)	3.69	-1.86***	-0.32
	(1.565)	(-7.713)	(-0.508)
Crisis	61.71	-7.78*	-11.73
	(1.560)	(-1.904)	(-0.906)
SBA Branch Share (t-1) * Crisis	1.34	1.74***	-0.13
	(0.450)	(3.482)	(-0.129)
Observations	23,052	23,052	23,033
R-squared	0.137	0.063	0.0143
Number of Counties	2,730	2,730	2,730
County FE	Yes	Yes	Yes
Local Banking Chars.	Yes	Yes	Yes
Local Econ Vars.	Yes	Yes	Yes

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 7- Future unemployment

The table displays coefficients from panel regression models of the county unemployment rate in year t+1. The estimated models include all variables from Table 5. Standard errors are clustered at the county level.

VARIABLES	(1) Unemployment (t+1)
SBA Branch Share (t-1)	0.12715**
	(2.514)
Crisis	18.51886***
	(15.057)
SBA Branch Share (t-1) * Crisis	-0.83676***
	(-8.804)
Ln(# Large Bank Branches)	0.17862***
	(8.055)
Ln(# Large Bank Branches * Crisis)	0.12266***
	(4.873)
HHI	-1.07691***
	(-9.153)
HHI * Crisis	0.10776
	(0.551)
Tier 1 Capital Ratio	-1.03206*
	(-1.760)
Tier 1 Capital Ratio * Crisis	-3.44411***
	(-4.749)
Mortgage Ratio	-0.15357
	(-0.800)
Mortgage Ratio * Crisis	2.04278***
	(10.458)
Ln(Median Inc.)	2.27351***
	(12.647)
Ln(Median Inc.) * Crisis	-1.53512***
	(-13.613)
Weighted HPI Growth	-6.66431***
	(-33.432)
Weighted HPI Growth * Crisis	4.13804***
	(8.319)
Unem. Rate	0.45762***
	(69.819)
Unem. Rate * Crisis	-0.09021***
	(-9.618)
Constant	-20.79144***
	(-10.917)
Observations	20,225
Number of Counties	2,730
R-squared	0.797
County FE	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8- Employment by firm size

The table displays coefficients from panel regression models of the natural log of employment for small firms with less than 20 employees (column 1) and large firms with more than 500 employees (column 2). The estimated models include all variables from Table 5. Standard errors are clustered at the county level.

VARIABLES	(1) Ln(Employment)- Small Firms	(2) Ln(Employment)- Large Firms
SBA Branch Share (t-1)	-0.02956***	-0.01127
	(-6.220)	(-0.704)
Crisis	0.00497	-0.08609
	(0.064)	(-0.402)
SBA Branch Share (t-1) * Crisis	0.01136**	-0.02185
	(2.041)	(-1.364)
Observations	22,989	22,901
R-squared	0.923	0.855
Number of Counties	2,728	2,724
County FE	Yes	Yes
Local Banking Chars.	Yes	Yes
Local Econ Vars.	Yes	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9- Hiring and separations rates for small and large firms
The table displays coefficients from panel regression models of the hiring rate (column 1) and separations rate (column 3) for small firms with less than 20 employees and large firms with more than 500 employees (columns 2 and 4). The estimated models include all variables from Table 5. Standard errors are clustered at the county level.

VARIABLES	(1) All Hiring- Small Firms	(2) All Hiring- Large Firms	(3) Separations- Small Firms	(6) Separations- Large Firms
SBA Branch Share (t-1)	-0.00216**	0.00073	-0.00370***	-0.00465**
	(-2.181)	(0.360)	(-4.746)	(-2.433)
Crisis	0.01676	0.05724*	-0.08362***	-0.07572**
	(1.158)	(1.710)	(-7.360)	(-2.400)
SBA Branch Share (t-1) * Crisis	0.00241**	-0.00509**	0.00097	-0.00087
	(2.033)	(-2.077)	(1.072)	(-0.365)
Observations	22,989	22,903	22,989	22,903
R-squared	0.0162	0.120	0.0397	0.104
Number of Counties	2,728	2,722	2,728	2,722
County FE	Yes	Yes	Yes	Yes
Local Banking Chars.	Yes	Yes	Yes	Yes
Local Econ Vars.	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10- Small and large establishment growth rate

The table displays coefficients from panel regression models of the growth rate for the number of small (column 1) and large (column 2) establishments. The estimated models include all variables from Table 5. Standard errors are clustered at the county level.

VARIABLES	(1) % Chg. Establishments- Small Firms	(2) % Chg. Establishments- Large Firms
SBA Branch Share (t-1)	-0.00696***	0.08297***
	(-3.657)	(3.655)
Crisis	0.08372**	0.92680**
	(2.477)	(2.429)
SBA Branch Share (t-1) * Crisis	0.00901***	-0.02398
	(3.570)	(-0.721)
Observations	23,052	14,115
R-squared	0.140	0.014
Number of Counties	2,730	1,920
County FE	Yes	Yes
Local Banking Chars.	Yes	Yes
Local Econ Vars.	Yes	Yes

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 11- SBA loan outcomes
The table displays coefficients from panel regression models of the 3-year default rate (columns 1 and 3) and % SBA loan charge off (columns 2 and 4). Standard errors are clustered at the county level.

VARIABLES	(1) SBA Loan Default Rate	(2) % SBA Loans Charged Off	(3) SBA Loan Default Rate	(4) % SBA Loans Charged Off
SBA Branch Share (t-1)			-0.06905***	-0.03307***
			(-5.044)	(-3.175)
Crisis	-0.92920***	-0.25670	-0.48482*	-0.09137
	(-3.932)	(-1.332)	(-1.855)	(-0.415)
SBA Branch Share (t-1) * Crisis			-0.00172	-0.00558
			(-0.079)	(-0.306)
Ln(# Large Bank Branches)			-0.03890***	-0.02353***
			(-6.721)	(-5.259)
Ln(# Large Bank Branches * Crisis)			0.01016**	0.00020
			(2.268)	(0.057)
HHI			0.14384***	0.13357***
			(3.791)	(4.579)
HHI * Crisis			-0.07439	-0.09313**
			(-1.287)	(-2.064)
Tier 1 Capital Ratio			-0.58729***	-0.33905***
			(-3.920)	(-3.434)
Tier 1 Capital Ratio * Crisis			-0.24859*	-0.12140
			(-1.674)	(-1.019)
Mortgage Ratio			-0.00716	0.00308
			(-0.166)	(0.100)
Mortgage Ratio * Crisis			0.10817**	0.08868**
			(2.424)	(2.433)
Ln(Median Inc.)	-0.31802***	-0.19944***	-0.04945	-0.00606
	(-8.927)	(-7.754)	(-1.141)	(-0.187)
Ln(Median Inc.) * Crisis	0.08378***	0.02326	0.03701	0.00505
	(3.897)	(1.325)	(1.542)	(0.252)
Ln(Population)	-0.41330***	-0.08537**	-0.35918***	-0.07912*
	(-6.922)	(-2.043)	(-5.900)	(-1.814)
Weighted HPI Growth	-0.40757***	-0.27390***	-0.36422***	-0.25048***
	(-10.082)	(-8.401)	(-8.477)	(-7.271)
Weighted HPI Growth * Crisis	0.07024	0.05729	0.03403	-0.01258
	(0.699)	(0.722)	(0.312)	(-0.146)
Unem. Rate	-0.03967***	-0.02320***	-0.03013***	-0.01663***
	(-31.040)	(-22.001)	(-20.048)	(-13.370)
Unem. Rate * Crisis	0.01381***	0.00707***	0.00762***	0.00296*
	(7.640)	(4.929)	(3.828)	(1.870)
Constant	8.31388***	3.29072***	4.97365***	1.21045**
	(14.281)	(8.163)	(7.611)	(2.548)
Observations	17,197	17,197	16,255	16,255
R-squared	0.147	0.0125	0.164	0.0164
Number of Counties	2,672	2,672	2,652	2,652
County FE	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 12- Instrumental variables

This table shows regression estimates for analyzing the effect of SBA branch share on credit volume to the smallest small businesses and employment for small (<20 employees) and large (>500 employees) firms using an instrumental variable approach as in Wooldridge section 18.4.1. Panel A shows the first-stage probit regression estimates at the bank level predicting SBA participation. I use the variables *House Committee on Small Business* and *Democrat Committee Member* as instruments. Also included are bank variables *Cash/total deposits, Ln(Gross Total Assets), ROA, Equity/Total Assets,* and *Non-performing loans/Total Loans*. Year fixed-effects are included. Panel B shows the final stage regression estimates after the predicted SBA participation from the first stage is aggregated to the county level and used as an instrument for SBA branch share. The estimated models include all variables from Table 5. Standard errors are clustered at the county level.

Panel A: First Stage	
	(1)
VARIABLES	SBA Participation
House Committee on Small Business Member (t-1)	-0.16***
	(-3.208)
Democrat Committee Member (t-1)	0.16*
	(1.790)
Constant	-4.61***
	(-22.749)
Observations	141,480
Number of Banks	13,010
Bank Variables	Yes
Year FE	Yes

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Panel B: 2SLS Final Stage			
	(1)	(2)	(3)
VARIABLES	Volume to firms < $1 Mil. Rev	Ln(Emp.) Small Firms	Ln(Emp.) Large Firms
SBA Branch Share	-1.06***	-0.55***	0.22
	(-9.697)	(-7.927)	(1.547)
SBA Branch Share * Crisis	0.18***	0.08**	-0.01
	(3.534)	(2.353)	(-0.152)
Crisis	-0.08	0.15	-0.16
	(-0.430)	(1.337)	(-0.705)
Observations	23,052	22,989	22,901
R-squared	-1.182	-0.714	0.039
Number of Counties	2,730	2,728	2,724
County FE	Yes	Yes	Yes
Local Banking Chars.	Yes	Yes	Yes
Local Econ Vars.	Yes	Yes	Yes
First-Stage Kleibergen-Paap rk Wald F Statistic	56.550***	54.790***	52.869***

Robust z-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 13- Including additional local bank variables
The table displays coefficients from panel regression models of the credit volume to the smallest small businesses (column 1) and employment for small (<20 employees) (column 2) and large (>500 employees) (column 3) firms. The estimated models include all variables from Table 4 in addition to the weighted average equity ratio, ROA, non-performing loans ratio, and cash-to-deposits ratio of local banks, along with their interactions with the crisis dummy, as defined in Berger and Roman (2016). Standard errors are clustered at the county level.

VARIABLES	(1) Volume to Firms < $1 Mil. Rev. per capita	(2) Ln(Emp.) Small Firms	(3) Ln(Emp.) Large Firms
SBA Branch Share (t-1)	-0.03***	-0.03***	-0.01
	(-4.664)	(-5.470)	(-0.630)
Crisis	-0.46***	-0.02	0.00
	(-4.907)	(-0.316)	(0.009)
SBA Branch Share (t-1) * Crisis	0.04***	0.01**	-0.02
	(5.059)	(2.291)	(-1.288)
Bank Profitability	0.17	0.48***	0.71
	(0.831)	(3.561)	(1.533)
Bank Liquidity	-0.53***	-0.10**	-0.02
	(-10.232)	(-2.345)	(-0.127)
Non-Perf. Loans Ratio	0.05	0.34***	0.05
	(0.676)	(6.427)	(0.306)
Bank Profitability * Crisis	-0.83***	-0.73***	-0.55
	(-3.421)	(-4.529)	(-1.025)
Non-Perf. Loans Ratio * Crisis	-0.78***	-0.71***	0.83***
	(-5.883)	(-6.845)	(2.742)
Bank Liquidity * Crisis	0.03	0.08	0.02
	(0.498)	(1.358)	(0.151)
Constant	2.29***	1.82***	-6.44***
	(9.754)	(3.504)	(-4.537)
Observations	23,039	22,976	22,889
R-squared	0.326	0.254	0.067
Number of Counties	2,730	2,728	2,724
County FE	Yes	Yes	Yes
Local Banking Chars.	Yes	Yes	Yes
Local Econ Vars.	Yes	Yes	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14- Time-invariant SBA branch share

The table displays coefficients from panel regression models of the volume of small business loans < $1 million per capita (column 1) and volume (column 2) of small business loans to firms with less than $1 million in annual revenues per capita. SBA market presence is measured as of the year 2003. The estimated models include all variables from Table IX. Standard errors are clustered at the county level.

VARIABLES	(1) Volume per capita	(2) Volume to firms < $1 Mil. Rev.
SBA Market Presence 2003	0.16***	0.08***
	(6.289)	(5.706)
Crisis	-0.90***	-0.52***
	(-5.595)	(-5.543)
SBA Market Presence 2003 * Crisis	0.01	0.01*
	(0.576)	(1.666)
Observations	23,033	23,033
R-squared	0.277	0.201
Number of Counties	2,729	2,729
County FE	No	No
Local Banking Chars.	Yes	Yes
Local Econ Vars.	Yes	Yes

Robust z-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 15- Predicted SBA prevalence

The table displays coefficients from panel regression models of the year ahead SBA Branch Share. The estimated models include all variables from Table 5. Standard errors are clustered at the county level.

VARIABLES	(1) SBA Branch Share (t+1)
SBA Branch Share	0.28***
	(20.677)
Crisis	-0.54***
	(-3.894)
SBA Branch Share * Crisis	-0.07***
	(-6.338)
Observations	20,319
Number of Counties	2,730
R-squared	0.183
County FE	Yes
Banking Chars.	Yes
Local Econ Vars.	Yes

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 16- Alternative crisis definition

The table displays coefficients from panel regression models of the total volume (column 1), and the volume small business loans to firms with less than $1 million in annual revenues per capita (column 2). The crisis in this case is defined as beginning in July of 2007 and ending in June of 2010. The estimated models include all variables from Table 5. Standard errors are clustered at the county level.

VARIABLES	(1) Ln(Volume)	(2) Ln(Volume) to < $1 Mil.
SBA Branch Share	-0.03835***	-0.06363***
	(-5.578)	(-5.261)
Crisis (Jul. 2007 – Jun. 2010)	-0.29891***	-0.24922*
	(-3.480)	(-1.724)
SBA Branch Share * Crisis (Jul. 2007 – Jun. 2010)	0.02958***	0.02337**
	(4.632)	(2.333)
Ln(# Large Bank Branches)	0.00232	-0.00440
	(0.799)	(-0.957)
Ln(# Large Bank Branches * Crisis)	-0.01157***	-0.01482***
	(-7.622)	(-5.691)
HHI	0.02922	-0.01409
	(1.459)	(-0.516)
HHI * Crisis	-0.02341*	0.01574
	(-1.791)	(0.809)
Tier 1 Ratio	-0.53103***	-0.70529***
	(-6.490)	(-6.586)
Tier 1 Ratio * Crisis	0.03064	-0.03740
	(0.804)	(-0.683)
Mortgage Ratio	-0.00507	-0.05143
	(-0.180)	(-1.264)
Mortgage Ratio * Crisis	-0.00119	0.03842*
	(-0.082)	(1.719)
Ln(Median Inc.)	-0.18865***	-0.10818***
	(-8.712)	(-2.679)
Ln(Median Inc.) * Crisis	0.02343***	0.01765
	(2.964)	(1.313)
Weighted HPI Growth	-0.00844	0.13596**
	(-0.236)	(2.433)
Weighted HPI Growth * Crisis	-0.02854***	-0.05542***
	(-27.707)	(-31.559)
Unem. Rate	0.00810***	0.01030***
	(10.963)	(8.674)
Unem. Rate * Crisis	2.54209***	2.24884***
	(10.964)	(5.245)
Constant	-0.03835***	-0.06363***
	(-5.578)	(-5.261)
Observations	23,052	23,052
R-squared	0.320	0.339
Number of Counties	2,730	2,730
County FE	Yes	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1