Small Bank Comparative Advantage in Alleviating Financial Constraints and Providing Liquidity Insurance Over Time

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Abstract

This paper uses novel survey data on U.S. small businesses from 1993-2012 to examine whether small banks are (still) better able to provide financial support to small businesses than large banks. We show that small banks' comparative advantage is stronger when local economic conditions are worse, and that it has not deteriorated over time. While both small and large banks curtailed lending to small businesses during the recent financial crisis, small banks provided more support to small businesses following the Lehman Brothers failure in regions with exposure to banks dependent on the asset-backed commercial paper (ABCP) markets. On balance, the results suggest that small banks continue to alleviate financial constraints for small businesses, likely through providing liquidity insurance to relationship borrowers in spite of recent improvements in transactional lending technologies.

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1. Introduction

Small businesses are often financially constrained due to informational asymmetries and other frictions (e.g., Hubbard, 1998; Carpenter and Petersen, 2002), and are therefore unable to obtain all the external funds required to fully satisfy their financial needs (e.g., Fazzari, Hubbard, and Petersen, 1988). Because small businesses are critical for economic growth,[1] there is social value in relieving their financial constraints and providing them with liquidity during economic downturns. Banks as relationship lenders may alleviate frictions that reduce credit availability to these borrowers (e.g., Boot and Thakor, 2000), and their comparative advantage lies in their ability to use soft, qualitative information. The use of soft information is typically viewed as being most pronounced in the case of small banks that are located relatively close to their customers (e.g., Petersen and Rajan, 2002).[2] However, some have argued that advances in information technology like small business credit scoring, and deregulation of banks that allows them to compete more effectively over large geographic areas, have reduced the importance of soft information and improved the ability of large banks and others to serve small businesses (Berger and Udell, 2006). It is therefore unclear if small banks still have a comparative advantage in small business lending, and whether they are better able to help their borrowers during adverse economic periods.

In this paper, we examine small bank comparative advantages and how they change during local economic downturns. Specifically, we ask: Are small banks (still) better able to provide financing to small businesses than large banks, and how has this ability changed over the past two decades? How does this comparative advantage change during periods of economic distress, and

[1] Small businesses accounted for 46% of private, non-farm gross domestic product in the United States in 2008 (Kobe, 2012) and were responsible for 63% of net new jobs created between 1993 through 2013 (Headd, 2014).

[2] Small banks may be superior at handling soft, qualitative information that is difficult to communicate within large, banking organizations with multiple layers of management (Berger and Udell, 2002; Stein, 2002; Liberti and Mian, 2009). Large banks may also suffer from diseconomies of scope when combining lending technologies that are based on hard, quantitative information, such as credit scoring, with those using soft, qualitative information, such as relationship lending (e.g., Williamson, 1988).

during the recent financial crisis? Consistent with the existing literature, we document (using better small business data spanning a longer time period) that small businesses that have greater access to small banks were less prone to experiencing financing difficulties over the past two decades. Importantly, we show that that small banks' comparative advantage increases when local economic conditions are worse. We assess this effect during the recent financial crisis period by exploiting local variation in exposure to the asset-backed commercial paper (ABCP) markets following the failure of Lehman Brothers in September 2008. We show that small businesses in regions with ABCP exposure were more prone to encountering financing difficulties, providing evidence of funding shocks for large banks that relied on the ABCP markets and that they were not able to fully retain some small business customers. We then show that accessibility to small banks in these regions mitigated this effect. These results suggest that small banks still serve a valuable role in providing liquidity to small firms, particularly during local economic downturns, presumably when access to external financing for these firms is critical.

We use novel survey data on a representative sample of small businesses from the Small Business Economic Trends (SBET) survey, which is conducted by the National Federation of Independent Businesses (NFIB), the largest U.S. small business organization with over 350,000 small business members.[3] The survey randomly samples firms on a monthly basis from 1993 to 2012, and allows us to overcome data limitations faced in the extant literature on small business finance.[4] In particular, we are able to directly observe *managerial perceptions* of financial constraints and investment opportunities, and is critical since a major empirical challenge in tests

[3] Members include independent businesses and exclude franchises.
[4] The data also affords other, important advantages. First, the SBET dataset is much more representative of small businesses as a whole than the commonly used Survey of Small Business Finance (SSBF), which includes relatively large businesses, and the Kauffman Financial Survey (KFS), which only includes start-ups. Second, we are able to study firms' survey responses over a much broader sweep of history using a long, continuous monthly time series from 1993 to 2012 instead of using data collected every 5 years (SSBF) or only since 2004 (KFS), as in the other data sets.

of financial constraints is accurately measuring those constraints and controlling properly for credit demand, making them susceptible to omitted variable biases. The survey directly asks borrowing firms whether their borrowing needs are satisfied, allowing us to avoid using indirect measures of constraints, such as loan balances, but instead capture the extent to which firms are able to obtain credit on acceptable terms when they really want it. The survey also provides details on the firm's expectations about future firm performance and business conditions, enabling us to create direct proxies for credit demand. Finally, the survey also asks firms whether they borrow regularly (i.e., at least every three months). This allows us to distinguish effects between regular borrowers, i.e., firms that are more likely to have strong banking relationships and rely on lines of credit, and non-regular borrowers, i.e., those that borrow less frequently and so may be more likely to shop around for their financing.

To quantify the comparative advantage of small banks, we regress a dummy variable that equals one if a firm that recently borrowed or attempted to borrow is financially constrained (i.e., it perceives its borrowing needs as not satisfied) on the local market share of small banks (i.e., the proportion of branches belonging to small banks within a 50-kilometer radius of the firm).[5] The coefficient on this small bank share variable measures the sensitivity of firm financial constraints to small bank share, and (inversely) captures the comparative advantage of small banks in satisfying the financial needs of their small business customers. We control for other local bank, local market, and firm characteristics, as well as industry and time fixed effects.

In our baseline specifications over the entire sample period, we find that small bank share is negatively associated with financial constraints. That is, firms with better access to small banks relative to large banks are better able to satisfy their financing needs. The estimates are statistically

[5] We view banks with gross total assets, or GTA,[5] up to $1 billion as small, in line with the usual definition of "community banks."

and economically significant. A one standard deviation increase in small bank share decreases the likelihood of financing difficulties by 2.1 percentage points for all borrowers, which is economically significant when compared to the overall proportion of borrowers reporting financing constraints of 15.5%. Consistent with intuition, the economic magnitudes are larger for non-regular borrowers, suggesting that firms with presumably weaker banking relationships are more sensitive to credit availability conditions in local banking markets. We offer a number of robustness checks that suggest the influences of omitted variable and sample selection biases on the point estimates are unlikely to be large. We also find similar results using alternative measures of financial constraints from the survey.

We next examine how small banks' ability to provide liquidity to small firms has changed during periods of adverse economic conditions over time. We measure local economic conditions using the local unemployment rate and per-capita wage for the county in which the firm is located, and estimate how small banks' comparative advantage varies across local economic conditions using interaction terms between small bank share and the local economic proxies.[6] These results suggest that small banks' comparative advantage increases when local economic conditions worsen, consistent with small banks providing more liquidity support to small businesses than large banks do during these periods.[7] We find similar results when controlling for adverse economic conditions at the national level.

One potential concern is that this result could be driven by the earlier part in the sample period since the existing literature argues that small banks' comparative advantage has decreased over time due to technological advances in transactional lending and deregulation. We show that

[6] Because economic downturns may also be associated with poor bank funding conditions, we also include interaction terms between small bank share and local bank capitalization and the federal funds rate level.
[7] One possible explanation is that small banks may have a greater willingness to renegotiate loan terms during these periods, but the data do not allow us to directly confirm this.

this concern is unwarranted. Over our entire sample period, the advantage is stable across normal and adverse economic periods. That is, there is no long-term downward trend in small banks' comparative advantage in serving small businesses.

Finally, we examine how the comparative advantage of small banks was affected during the recent financial crisis by exploiting local variation in funding shocks due to disruptions in the ABCP markets following the collapse of Lehman Brothers in September 2008. We start by showing that aggregate small business lending decreased at both small and large banks during this time, and that the reduction in lending was greatest at large banks that depended on the ABCP markets for short-term financing. This is consistent with existing evidence of sharp reductions in small business lending during the financial crisis (Greenstone, Mas, and Nguyen, 2014). Ivashina and Scharfstein (2010) and Chodorow-Reich (2014) document similar patterns in new loans to relatively larger firms following the collapse of Lehman Brothers, and find that it was contributed by bank liquidity issues due to the disruptions in the short-term financing markets during that period. These results imply significant obstacles for firms that would have otherwise borrowed from constrained banks during this period.

We quantify local exposure of banks dependent on the ABCP markets right before the crisis, and focus on small banks' ability to extend credit to small businesses relative to other banks that did not depend on the ABCP markets across the affected regions. To avoid potential endogeneity concerns, we use pre-crisis variation in the local market share small banks relative to all banks that did not rely on the ABCP markets. We test for whether small banks' comparative advantage increased more in regions exposed to the ABCP markets relative to those with no exposure.

We show that small banks' comparative advantage increased significantly in regions with ABCP exposure while it did not in regions without exposure following the Lehman Brother failure. We confirm that this pattern did not exist in the pre-crisis period, suggesting that this shock did not arise from systematic, regional differences related to credit demand. Furthermore, we find that this effect is driven by non-regular borrowers. This is consistent with the literature that finds firms with access to credit lines were able to draw upon them during the financial crisis to smooth funding shortfalls (Campello et al., 2010; Acharya and Mora, 2015), and that relationship borrowers are more likely to utilize credit lines (Berger and Udell, 1995). This provides suggestive evidence that small banks still serve an important in providing liquidity to small businesses during adverse economic periods, particularly during the recent financial crisis.

The remainder of this paper is organized as follows. Section 2 describes the empirical design, data, and variable construction. Section 3 contains the main results. Section 4 examines small banks' comparative advantage during the crisis period. Section 5 concludes.

2. Methodology and Data

This section begins by discussing the empirical design, followed by a detailed description of the data. Next, the baseline regression models are discussed. Table 1 provides details about the variables used in the analysis and shows summary statistics.

2.1 Empirical Design

We use the following OLS regression model to quantify small banks' comparative advantage in small business lending:

$$FinancialConstraints_{i,t} = \beta_0 + \beta_{CompAdv}\, SmallBankShare_{i,t}$$

$$
\begin{aligned}
&+ \beta_1 \textit{ Other Local Bank, Market Characteristics}_{i,t} \\
&+ \beta_2 \textit{ Firm Characteristics}_{i,t} \\
&+ \eta_{ind} + \tau_t + \varepsilon_{i,t}
\end{aligned}
$$

The key dependent variable is *FinancialConstraints*. Our main proxy, *NotSatisfied*, is a dummy variable that is coded as one for firms responding "no" to the question "During the last three months, was your firm able to satisfy its borrowing needs?," and zero if the response is "yes." Firms that did not borrow or try to borrow over the last three months do not answer this question, so that we may focus on firms that tried to get external financing. This is important because these firms have borrowing needs that may or may not have been satisfied. In the rest of the paper, we refer to these firms collectively as "borrowers" for ease of exposition. Firms that did not try to borrow are excluded from the analyses, which facilitates interpretation because it is ambiguous whether these firms are constrained or alternatively did not need seek bank financing. For most of our analyses we distinguish between regular and non-regular borrowers, those that answer "yes" and "no," respectively, to the question "Do you borrow at least once every three months?" We split the sample because regular borrowers are more likely to have established stronger banking relationships and thus the share of small banks in the market may be less relevant to their borrowing needs satisfaction.

The key explanatory variable of interest is *SmallBankShare,* the proportion of total bank branches within a 50 kilometer radius of the firm belonging to small banks.[8] Banks with gross total assets (GTA) up to $1 billion in 2005 real dollars are coded as small banks because this is the common definition of community banks, and others are coded as large banks.[9] To calculate the

[8] Petersen and Rajan (2002) examines the distance between firms and their lenders over the 1973-1993 time period. The 50 kilometer radius threshold used in this paper is between the mean (70 kilometers) and the median (7 kilometers) distance. We also examine distance thresholds of 40 and 100 kilometers, and find similar results.
[9] GTA equals total assets plus allowances for loan and lease losses and the allocated risk transfer. GTA may be considered a superior measure of the size of the balance sheet than total assets, which excludes the latter items that are part of the balance sheet that must be financed.

distance between the firm and a bank branch, we use the centroid of the 3-digit ZIP code of the firm (the only firm location data available in the survey) and the centroid of the 5-digit ZIP code of the bank branch in the most recent SoD data). The haversine formula is then used to calculate the distance between each firm and bank branch.[10] The coefficient on *SmallBankShare*, $\beta_{CompAdv}$, inversely captures small bank comparative advantage, and can be interpreted as the marginal impact of access to small banks on firms' financial constraints.

The control variables, discussed in Section 2.3, include other local bank, local market, and firm characteristics, which include survey responses that directly correspond with managerial perceptions of the firm's investment opportunities and credit demand. We also include industry fixed effects (η) based on ten industry groupings available in the survey to purge the influence of omitted time-invariant characteristics of industries,[11] and time fixed effects (τ) based upon year-month intervals to purge the financing outcome measures of aggregate factors. Because the model residuals (ε) are unlikely to be independent across time and location, we use two-way clustered standard errors on those dimensions.

2.2. Data

The small business data used in our analyses are collected by the NFIB in its SBET survey monthly from June 1993 to December 2012.[12] The NFIB randomly selects survey participants from its

[10] The haversine formula that estimates the kilometer distance between locations A and B can be calculated as:
$d_{A,B} = 2 R \arcsin([\sin^2(0.5(Y_A-Y_B)) + \cos(Y_A) \cos(Y_B)\sin^2(0.5*(X_B-X_A))]^{1/2})$
where (X_A,Y_A) and (X_B,Y_B) are the coordinates for locations A and B, respectively, and R is the Earth radius, or 6,356.752 kilometers.

[11] The industry classifications are self-reported, and include agriculture, retail, wholesale, transportation, manufacturing, construction, professional, services, financial, and other.

[12] Data are available for a longer time period: on a quarterly basis from 1973:Q1 until 1985:Q4 and on a monthly basis from 1986:M1 onward. June 1993 is chosen as the start of the sample period given that firm location information (3-digit ZIP code) is unavailable prior to that date.

members. The number of respondents is approximately 865 per month over the sample period and the key dependent variable, *NotSatisfied*, is available for about 400 respondents per month, the firms that classify themselves as borrowers.[13,14] The identities of the firms are confidential.

First, the survey firms are much more representative of small businesses as a whole than the commonly used Survey of Small Business Finance (SSBF), which includes relatively large businesses, and the Kauffman Financial Survey (KFS), which only includes start-ups.[15] Second, we are able to study firms' survey responses over a much broader sweep of history using a long, continuous monthly time series from 1993:M6 to 2012:M12 instead of using data collected every 5 years (SSBF) or only since 2004 (KFS), as in the other data sets. Third, it includes perceptions on different aspects of the firm's operations, including the firm's perceived financial constraints, economic outlooks, and general business conditions. Fourth, the survey provides firm characteristics that are readily available to outside creditors, such as basic details about the firm, including the legal form of the business, previous revenues, and the number of employees. It also reports the industry in which the firm operates. Importantly, we are also able to identify the location of the firm with a reasonable level of precision.

For each firm, we identify nearby branches of banks using the FDIC's annual Summary of Deposits (SoD) dataset from June 1993 to June 2012. We collect branch-level information on each bank, including its branch location and deposit size. Additionally, we obtain quarterly commercial bank information from the Call Reports and, if the bank belongs to a bank holding company, the

[13] The average number of respondents per month increases slightly over the sample period from 855 (1993-2002) to 872 (2003-2012). The number of observations that are used in the analysis increases in a similar fashion.

[14] We discuss possible sample selection bias issues in Section 3.3.

[15] Specifically, the SSBF used in most of the literature only surveys firms every five years and includes businesses up to 500 full-time equivalent employees. Berger, Cerqueiro, and Penas (forthcoming) use the KFS, a panel dataset that only includes recent information on start-up firms. Hence, both include firms that might not be considered as representing small businesses as a whole. In contrast, the SSBF used in this paper surveys firms every month and focuses on firms that self-identify as small businesses.

Y-9C data from 1993:Q2 to 2012:Q3. The Call Report, Y-9C, and SoD datasets are linked using the RSSD9001 identifier supplied in these datasets. Finally, county-level population, wage and unemployment rate data are obtained from the Bureau of Labor Statistics.

2.3. Control Variable Construction

We include other local bank characteristics that may affect the supply of credit as controls. Bank capitalization *EqRat*, is the average bank equity to GTA of all banks within a 50 kilometer radius of the firm. Bank illiquidity, *IlliquidityRat*, is the average amount of liquidity created by the bank to GTA of all banks within a 50 kilometer radius, calculated using the preferred measure described in Berger and Bouwman (2009).[16] Bank concentration, *DepositHHI*, is the Herfindahl-Hirschman index of deposit share of all banks within a 50 kilometer radius. *Branch/Pop* is the ratio of the number of branches within a 50 kilometer radius to local population.[17] *FewBanks* is a dummy variable that takes a value of one if the number of banks within a 50 kilometer radius of the firm is below the lowest 10th percentile for a particular year. *Metro* is a dummy variable that equals one if the firm is located in a metropolitan area, and zero if it is in a rural area.[18,19] *CountyPop* is the population of the county where the firm is located.

[16] The ratio of liquidity creation to GTA is a measure of liquidity created by the bank relative to its assets. This is a measure of illiquidity because when banks create liquidity for the public, they are making themselves less liquid (e.g., by holding illiquid loans and dispensing liquid deposits).

[17] To measure local population, we use the average county-level population of all counties represented within a 50 kilometer radius of the firm.

[18] We do not have the precise location of the firm, so we cannot use the standard approach of directly assigning each firm to a Metropolitan Statistical Area (MSA) or New England County Metropolitan Area (NECMA) versus rural area. However, we do know each firm's 3-digit ZIP code. Our main approach therefore classifies a firm as being located in a metropolitan area if more than 50% of 5-digit ZIP codes within the firm's 3-digit ZIP code are located in an MSA or NECMA; otherwise, it is classified as rural. The survey also asks respondents whether the firm is located in a metropolitan or rural region and using respondent-supplied classifications we obtain similar results.

[19] Metropolitan regions may correlate with profitability in investment opportunities relative to rural regions. Since firm characteristics and banking market dynamics may differ considerably across metropolitan and rural markets, we also run the regressions separately for these areas and obtain qualitatively similar results.

We also include firm characteristics that may affect credit demand. Firm size may be related to investment opportunities. *ln(Sales)* is the natural log of one plus the lowest sales value of the sales category the firm belongs to, ranging from ($0 to $12,500) to over $1.25 million. *ln(Employees)* is the natural log of the lowest number of employees of the employee category the firm belongs to, ranging from "one" to "40 or more." The organizational status of the business may also influence firm financing decisions. *Corporation*, *Partnership*, and *Sole Proprietorship* are dummy variables that take the value of one if the firm is a corporation, a partnership, and a sole proprietorship or other, with *Sole Proprietorship* being the excluded category. Three firm characteristics relate to managerial expectations of future performance. Two capture managerial expectations regarding the firm's future performance. *ExpGenCond* is the firms' response to the survey question how general conditions are expected to change in the next six months on a five-point scale, ranging from "much worse" (-2) to "much better" (+2). *ExpSales* is their response to the question how sales will change in the next three months compared to the present period on a five-point scale, ranging from "much lower" (-2) to "much higher" (+2). A third characteristic captures actual sales difficulties the firm faced in the recent past. *ChSales* measures how current sales differ from sales over the past three months on a five-point scale, ranging from "much lower" (-2) to "much higher" (+2).

2.4. Summary Statistics

Table 1 Panel B displays summary statistics of all variables used in the main analysis for observations that have non-missing values for *NotSatisfied*. The sample mean of *NotSatisfied* is 15.5%. This figure is substantially lower for regular borrowers (12.8%) than for non-regular borrowers (22.4%). This difference is expected, since regular borrowers presumably have stronger relationships and therefore more often receive the financing they need. This may be due to the bank having more information on such borrowers (Petersen and Rajan, 1994; Berger and Udell, 1995) and/or the provision of liquidity insurance to regular borrowers (Berlin and Mester, 1999; Kashyap, Rajan, and Stein, 2005; Thakor, 2005).

The average proportion of small bank branches in close proximity to sample firms, or *SmallBankShare*, is 42.6%. Looking at the other local bank characteristics, the average bank appears to have substantial capital (mean *EqRat* of 9.6%), and is somewhat more illiquid on average than in Berger and Bouwman (2009), 0.42 here versus 0.34 there, possibly because we include more recent data when bank liquidity creation was expanding. The banks in our sample have typical concentration statistics (mean *DepositHHI* of 0.147 is in the moderately concentrated range). The sample mean of *Branch/Pop* of 0.001 suggests that the average banking market has slightly less than one branch per 1,000 population, which seems reasonable. The mean of *FewBanks* is essentially forced to be about 10%. The sample firms are almost evenly split between rural and metropolitan banking markets (53% *Metro*). The county-level population is right-skewed – its sample mean is 520,807 and median is 164,910.

Sample firms are generally very small. Average sales for each firm are approximately $329,000, while the sample median is $87,500. The average number of employees for each firm is approximately 11, while the sample median is 6. Approximately 69% of the firms are incorporated, while 6% are partnerships. The remaining 25% are sole proprietorships or are self-classified as "other." *ExpGenCond*, has a mean of 0.029, while the sample standard deviation is 0.772. This implies that firms on average expect the general conditions to improve somewhat, but there is considerable variation. *ExpSales* has a mean of 0.170, and *ChSales* has a mean of -0.023.

3. Main Results

This section begins by presenting the baseline specification of small bank accessibility on firm financial constraints, and performs a number of robustness checks. This is followed by tests on how small banks' comparative advantage changes with local economic conditions, and whether this relationship has changed over time.

3.1. Baseline Regression Model Results

Table 2 displays the results from the model that regresses *NotSatisfied*, our main measure of small business financial constraints, on *SmallBankShare*, the local market share of small banks, as well as controls. As noted above, small bank comparative advantage is captured (inversely) by the coefficients on *SmallBankShare*. Negative *SmallBankShare* coefficients imply that greater access to small banks is associated with reduced difficulties in satisfying financing needs and indicate the presence of comparative advantages. To ensure that the estimates are not driven by our choice of control variables, we include different sets of controls. If the *SmallBankShare* coefficients are stable across the specifications, the results are unlikely to be driven by unobservable firm heterogeneity. These models treat small bank comparative advantages as constant across economic conditions and over time, assumptions to be dropped later.

We begin by examining the estimates using the entire sample of borrowers in Panel A. When including only *SmallBankShare* plus year-month fixed effects (Column (1)), its coefficient is negative and statistically significant (estimate = -0.105, t-value = -11.42). This indicates that when small banks are more prominent in the local market, small businesses face significantly fewer financing constraints, consistent with the presence of small bank comparative advantages. The *SmallBankShare* coefficient remains stable when adding controls for other local bank and market characteristics (Column (2): estimate = -0.090, t-value = -9.28); and when instead controlling for different sets of firm characteristics and industry fixed effects (Column (3): estimate = -0.117, t-value = -13.51).

The *SmallBankShare* coefficient is also similar in Column (4), which includes all the control variables from specifications 2 through 3 (Column (4): estimate = -0.0854, t-value = -9.02). In Column (5), the time fixed effects are replaced with location (state) fixed effects to assess whether the explanatory power is driven by specific regions.[20] The *SmallBankShare* coefficient remains negative and statistically significant (Column (5): estimate = -0.71, t-value = -5.75). In the robustness checks, we focus on the full specifications from Columns (4) and (5).

The magnitudes of the *SmallBankShare* estimates are also economically significant. For example, focusing on the full specification from Column (4), a one standard deviation increase in *SmallBankShare* decreases the predicted value of *NotSatisfied* by 2.12 percentage points (13.72% of the sample mean). Similar figures obtain when using the model estimates from Column (5). Thus, the data strongly suggest comparative advantages for small bank in our sample firms.

The signs on the coefficients of the control variables are also generally consistent with intuition. Small firms are more financially constrained when there are relatively few banks in the area. They feel less constrained when they are larger in terms of number of employees or total sales, and expect better general conditions and/or higher past sales growth. The firm-level characteristics appear to capture credit demand well given that we expect it to correspond strongly with revenues in small businesses, and the adjusted R^2 substantially increases from Column (1) to (3).

[20] We use state fixed effects in favor of other, more granular spatial measurements, such as county level, given that we cannot observe firm identities and whether they respond to the survey more than once; and that some local areas are not represented consistently throughout every year of the sample period.

The results from Panel A are based on a pooled sample of respondents that borrow with different frequency. Firms that borrower regularly may have greater incentives to establish stronger banking relationships, while firms that borrow less frequently may be more likely to solicit multiple banks in search for better loan terms. Banks also have an incentive to establish relationships with frequent borrowers, given that they can reuse this information often. Additionally, regular borrowers are more likely to utilize credit lines, and so should be better able to smooth funding shortfalls over time. Panel B reruns the models from Columns (4) and (5) in Panel A separately for the regular borrower subsample (Columns (1) and (2)) and non-regular borrower subsample (Columns (3) and (4)).

The *SmallBankShare* coefficients are negative and statistically significant for both regular borrowers and non-regular borrowers with either time or location fixed effects. The economic magnitudes are sizeable in both subsamples: a one standard deviation increase in *SmallBankShare* decreases predicted *NotSatisfied* for non-regular borrowers by 3.69 percentage points (= 16.4% of the sample mean) and by 1.42 percentage points for regular borrowers (= 11.1% of the sample mean). The relatively larger magnitudes on the non-regular borrower subsample squares with intuition. Regular borrowers may have stronger banking relationships with their lenders, or may have access to lines of credit to provide liquidity following idiosyncratic cash flow shocks.

3.2. Robustness of the Baseline Regression Results

We next perform additional tests to assess the robustness of the baseline model results. Specifically, we examine whether the results change when using non-linear estimators, correcting for potential sample selection issues, and using alternative measures of financial constraints.

There is a concern that linear regression models are not limited to predicted values for *NotSatisfied* between 0 and 1. We address this issue by reestimating our models using logit specifications. The models include all the control variables from the baseline regression models, except for the fixed effects terms to avoid incidental parameter biases (Wooldridge, 2010). In untabulated estimates, we show that the marginal effects of *SmallBankShare* are negative and statistically significant, and are comparable to the OLS estimates in Table 2. These results suggest that our findings are robust to using a nonlinear model specification.

Next, we examine potential sample selection issues, given that the key dependent variables, *NotSatisfied*, is only available for 77,855 out of 166,186 total firm year-month observations included in the survey. The *SmallBankShare* coefficient estimates may be subject to sample selection bias given that not all firms respond to the questions related to borrowing. Those that did not answer the borrowing questions may be differentially related in terms of credit quality. These firms may be of weaker credits and may not have sought financing in the previous three months because they may are discouraged due to prior difficulty in obtaining bank financing. On the other hand, firms may not need external financing and so may not have sought bank financing in the previous three months. As a result, the model coefficients may be overstated or understated since the non-respondents have more or less difficulty in obtaining bank finance.

We model this account of sample selection using Heckman sample selection corrections on two dimensions. First, we consider firms without responses to the borrowing questions, or with missing values for *NotSatisfied.* Second, non-regular borrowers, representing 28.8% of all borrowers, may be prevented from obtaining financing on a more frequent basis because they have weaker credits than those that borrow regularly.[21]

[21] Another possible source of sample selection bias is that firms may be more likely to respond to the survey when they are experiencing greater difficulty overall. The survey sample may overweight these periods, and so affecting the model estimates. While this account may affect response rates overall (borrowers and non-borrowers), it is unclear whether it should affect the response rates of borrowers over time. In fact, the proportion of the sample that are borrowers slightly decreases following the start of the financial crisis in 2007, from 42% in the 2004-2006 sample period to 38% in 2008-2010. The decreasing trend may be due to other factors, namely firms discouraged from seeking financing.

In the first stage for the Heckman sample selection correction, we use all 166,186 observations in probit models to predict the likelihood of observing a non-missing value for *NotSatisfied*. The control variables included are identical to those from the baseline regression models, with *SmallBankShare* being the excluded variable. In the second stage, the full specification regression models are re-estimated with the inclusion of the inverse Mills ratio (*InverseMillsRatio1*). To address the second form of selection bias related to borrower frequency, we calculate another inverse Mills ratio (*InverseMillsRatio2*) based upon probit model estimates that predict the likelihood of observing a regular borrower within the sample of borrowers. We expect the coefficients on the inverse Mills ratios to be negative, given that the inverse Mills ratios correspond with firms with presumably stronger credits.

Table 3 displays the second-stage estimates for the specifications with the time fixed effects in Panel A. The *InverseMillsRatio1* coefficients are negative and statistically significant across all the models, while the *InverseMillsRatio2* coefficients are negative in Columns (2) and (3), but statistically significant only in Column (3). These results confirm the existence of the two accounts of selection biases discussed above. More important, the estimates on *SmallBankShare* are essentially unchanged from the OLS models. The bottom row displays the differences in the *SmallBankShare* estimates compared to the baseline regressions in Table 2. They show that the differences are not only small in magnitude, but are also statistically insignificant. The second-stage estimates using the location fixed effects are similar and displayed in Panel B.

Finally, we consider the robustness of the findings using three alternative measures of financial constraints related to credit availability and terms, which are not available for all borrowers and are more difficult to generalize. First, *ExpectedDifficulty* is a dummy variable that takes a value one if the firm expects to experience increased financing difficulty in the next three months.[22] The *ExpectedDifficulty* measure is only available for regular borrowers, and presumably relates to short-term debt financing. Second, *LoanSpread* is the loan interest rate paid minus the 3-month Treasury bill yield for the month during which the survey was conducted.[23] The survey does not include information about the type or maturity of the loan, so better maturity matching is not possible. The *LoanSpread* measure is available for most of the firms that respond to the question used to construct the *NotSatisfied* measure, and so are available for a subset of both regular and non-regular borrowers. Third, *RateChange* is an ordinal variable measured on a 5-point scale, ranging from -2 for "much lower", 0 for "no change", and 2 for "much higher" loan interest rates over the previous quarter.[24] The *RateChange* measure is only available for regular borrowers, and presumably relates to short-term debt financing whose loan rates are more likely to change. Examination of changes in loan interest rates is informative given that we cannot observe loan type or maturity in the *LoanSpread* measure.

Regressions that use these dependent variables are subject to potential sample selection bias just like our main regressions. To see that, note that *LoanSpread* is available for most firms that responded to the question used to construct the *NotSatisfied* measure, while *ExpectedDifficulty* and *RateChange* are only available for a subset of regular borrowers. To address this, we perform Heckman corrections as well based upon the availability of the dependent variable across all sample respondents. Additionally, we also include a Heckman correction related to whether the firm borrows regularly similar to Table 3.

[22] Specifically, the measure is based upon the question: "Do you expect to find it easier or harder to obtain your required financing during the next three months?"
[23] Specifically, the measure is based upon the question: "If you borrowed within the last three months for business purposes, and the loan maturity (payback period) was 1 year or less, what interest rate did you pay?"
[24] Specifically, the measure is based upon the question: "If you borrow money regularly (at least once every three months) as part of your business activity, how does the rate of interest payable on your most recent loan compare with that paid three months ago?"

Table 4 shows that the specifications that take sample selection into account (even-numbered columns) are very similar to those that do not (odd-numbered columns), so we focus our discussion here on the ones that do not. In all the regressions, all control variables from the baseline regression models are included, though not reported, as well as time fixed effects.[25] Column (1) displays the estimates using *ExpectedDifficulty* as the dependent variable. The *SmallBankShare* coefficient is negative and statistically significant, suggesting greater ease in obtaining financing in the near future if there are more small banks in the area. The coefficient on *SmallBankShare* in the *LoanSpread* model (Column 3) is also negative and statistically significant, suggesting that small firms pay lower spreads when there are more small banks in the area. However, the economic magnitude is small – the change in *LoanSpread* implied by Column (3) due to a one standard deviation increase in *SmallBankShare* is 0.02 percentage points, which is small compared to the mean *LoanSpread* of 5.04%. Finally, the *SmallBankShare* coefficient in the *RateChange* model (Column (5)) is also negative and statistically significant, suggesting that greater access to small bank financing is associated with bigger drops and smaller increases in loan interest rates over the previous quarter. In contrast to the *LoanSpread* results, the *RateChange* results appear economically significant: the change in the *RateChange* measure implied by Column (5) due to a one standard deviation increase in *SmallBankShare* is 0.135, which is large compared to the mean *RateChange* of 0.13.

These results generally confirm that greater small bank presence is associated with improved credit availability and credit terms. While statistically significant but not always

[25] We only consider time fixed effect specifications here given that some of the dependent variables that are related to loan price terms may vary significantly over time due to other factors. However, in untabulated estimates, the results are similar when using location fixed effects instead, though the *SmallBankShare* estimates in the *RateChange* model is insignificant but remains negative.

economically significant, the results are consistent overall with the baseline regression model results.

3.3. Comparative Advantages Across Local Economic Conditions and Time

In this section, we modify the baseline regression models to assess how small banks comparative advantage vary across periods with different economic conditions, and examine whether the results differ by borrower type. This is followed by tests to assess how these effects may have changed over the sample period.

We adjust the baseline regressions by including *SmallBankShare* independently as well as interacted with several local and nationwide measures of economic conditions.[26] We consider the local measure to be our main proxy because local shocks are more likely to be relevant to small businesses than nationwide indicators. Additionally, small banks may be more sensitive to local conditions, while some of the large banks may be more sensitive to national conditions.

Our main proxies for local economic conditions are the county-level unemployment rate in the county in which the firm is located ($Unemployment_{County}$) and the natural log of one plus the per-capita wage ($Wage_{County}$). We expect poorer, local economic conditions to increase small bank comparative advantages since small banks tend to engage in relationship lending, and that relationship lenders may provide liquidity insurance to their relationship borrowers during these periods. Additionally, transactional lending technologies, such as credit scoring models, which tend to be used more by large banks, may become less effective during these periods.

[26] For all continuous interaction variables, both *SmallBankShare* and the interaction variables are mean-centered before calculating the interaction term to minimize the influence of multicollinearity (Wooldridge, 2010). Control variables from the full specification from Column (6) in Table 2 are also included (coefficients not shown).

To ensure that we capture the effects of different economic conditions on small banks' comparative advantage rather than differential credit demand, we include the baseline control variables. Additionally, we control for bank funding factors related to monetary policy and local bank capitalization, given that they may also correspond economic conditions. First, monetary policy changes over time with policymakers' stances on aggregate economic conditions. The existing literature shows that small banks' lending and liquidity creation are more affected by monetary policy than large banks', given their limited access to non-deposit forms of external financing (e.g., Kashyap and Stein, 2000; Berger and Bouwman, 2014). We proxy for monetary policy using the federal funds rate (*FedFundsRate*) at the end of each month, which is targeted by the Federal Reserve as its primary monetary policy tool. We include the federal funds rate as an independent variable as well as its interaction with *SmallBankShare*. We expect that when the federal funds rate is higher, it will reduce lending by small banks more than by large banks, and hence small banks comparative advantage will be lower. Second, bank capital has been shown in the literature to be an important factor in bank lending and liquidity creation (e.g., Boot and Thakor, 2000; Berger and Bouwman, 2009). We include the average capital ratio within a 50 kilometer radius of the firm, both independently and interacted with *SmallBankShare*.

Table 5 shows the results when including the local economic proxies and their interaction terms with the time fixed effects in Columns (1)-(3) and location fixed effects in Columns (4)-(6). In Column 1, the uninteracted *SmallBankShare* coefficient remains negative and significant even after the inclusion of the local economic condition interaction terms. This suggests that small bank comparative advantages also exist during normal periods. Poorer local economic conditions appear to magnify the *SmallBankShare* coefficient in terms of local unemployment rates and per-capita wages in Column (1). The county-level unemployment rate interaction term is negative and statistically significant, while the county-level per-capita wage interaction term is positive and significant. The results suggest that small banks are better able than large banks to support small businesses during these periods of worse economic conditions. The results are similar for each borrower type, though slightly stronger for the non-regular borrower sample. The results are unlikely to be driven by a few regions, given that the specifications using location fixed effects produce similar in Columns (4)-(6).

The economic magnitudes implied by the Column (1) estimates are also significant. The marginal effect of increasing *SmallBankShare* by one standard deviation in regions with a county unemployment of 6.0% (sample mean) is 1.70 percentage points in the full sample. The same for regions with a county unemployment rate of 8.7% (one standard deviation above the sample mean) is 2.36 percentage points. In other words, small bank comparative advantages increases by approximately 40% during periods of poor economic conditions. These estimates are slightly larger using the model parameters from Column (4) and are comparable for each borrower subsample.

The model estimates on the other variables are also interesting. The coefficients on the local economic proxies suggest that financial constraints increasing during periods of poorer economic conditions. While credit demand may decrease during these periods due to less profitable investment opportunities or increased credit risk, the results are consistent with bank lending opportunities decreasing during these periods. While the interaction term coefficients between the average bank equity ratio are not significant, the interaction term coefficients between *FedFundsRate* and *SmallBankShare* are positive and significant, as expected.

We also consider proxies for nationwide economic conditions to help isolate local economic shocks unrelated to national trends. Specifically, we include the national unemployment rate (*Unemployment*$_{National}$) and the natural log of one plus the per-capita, national total wage (*Wages*$_{National}$) along with their interaction terms with *SmallBankShare*. Note that these measures are subsumed in the models with the time fixed effects though their interaction terms with *SmallBankShare* are not.

The results are robust even after controlling for national economic proxies to account for aggregate trends. In Column (1) of Table 6, we replace the local proxies with the national ones in the model with the time fixed effects. The results are comparable for the interaction terms related to the national unemployment rate and per-capita wage. When including both sets of proxies in Column (2), the results on the local economic proxies remain similar in terms of sign and statistical significance. Using location fixed effects instead of time fixed effects in Columns (3)-(4) yield similar results.

Of the national proxies, the interaction term on the national unemployment rate remains significant in the full specifications of Table 6. The estimates on the interaction term are substantially larger than those based upon local unemployment rates. Given that national economic conditions should be more relevant for larger banks, the results provide supportive evidence that large banks reduce support to small businesses when national conditions worsen. This could be because credit scoring models may incorporate aggregate economic conditions or because of cyclicality in lending focus of large banks. The results on local economic conditions could be driven by enhanced support by small banks, as they may be able to later extract rents in loan negotiations related to lock-in effects, or reduced support by large banks, if credit scoring model incorporate local economic conditions and are used in lending considerations.

While we control for credit demand, the results may be susceptible to omitted variable biases if its impact on financial constraints are amplified when local economic conditions worsen.

For example, negative shocks to firm revenues may be more painful during economic downturns than normal periods. To allay these concerns, we rerun the regression models including interaction terms between the *ln(Sales)*, *ExpSales*, and *ChSales* with the local economic proxies. In untabulated results, we find that the coefficients on the *SmallBankShare* terms remain virtually unchanged after inclusion of the additional control variables.

Overall, the results suggest that small banks are better able to provide liquidity insurance to small businesses over our sample period. Since the literature argues that small banks' comparative advantage has decreased over time due to technological advances and deregulation, one potential concern is that our results are driven by the earlier part of our sample period. To address this, we do the following. We examine whether there is a time trend in the *SmallBankShare* coefficient by adding an interaction term between *SmallBankShare* and a time trend variable, or *SmallBankShare* × *Trend*.[27] The time trend is measured as the number of years since the start of the sample period (e.g., *Trend* takes on a value of 0.083 for 1993:M7, one month after the start of the sample period). The trend could represent technological change and deregulation that may favor large banks. If small bank comparative advantages have decreased over the sample period, then the *SmallBankShare* × *Trend* coefficient should be positive.

We are also interested in how small bank comparative advantages during economic downturns have changed over the sample period. To address this, we do the following. We create triple interaction terms between *SmallBankShare*, the local economic proxies, and the time trend variable. If small banks' comparative advantage during economic downturns has diminished over time, we expect the coefficient on the triple interaction term to be positive for *SmallBankShare* ×

[27] Another approach would be to perform the same tests on sample splits for the first and second half of the sample period. We find that the results remain in each of the subsamples.

UnemploymentCounty × *Trend* and negative for *SmallBankShare* × *UnemploymentCounty* × *Trend*.

Columns (1) and (3) of Table 7 presents the results. The models include the baseline model control variables, the bank funding interaction terms, and the national economic interaction terms, but are not reported to conserve space. The *Trend* × *SmallBankshare* interaction term is not statistically significant for either specification, suggesting that small banks' comparative advantage has not changed significantly over time. In Columns (2) and (4), the triple interaction term coefficients are also statistically insignificant for both sets of local economic proxies. On the other hand, the interaction terms between *SmallBankShare* and each of the local proxies remain statistically significant across all specifications. The results suggest that small bank comparative advantages have not changed significantly during normal and distressed economic periods.

4. The Effects of Local ABCP Market Exposure during Recent Financial Crisis

In this section, we examine how small banks' comparative advantage was affected by a specific event during the recent financial crisis. Disruptions in the asset-backed commercial paper (ABCP) markets in August 2007 and following the collapse of Lehman Brothers in September 2008 dried up short-term funding liquidity in a number of large banks. Kacperczyk and Schnabl (2010) show that, following both events, the total commercial paper outstanding decreased while spreads over the Federal Funds rate increased sharply, namely for ABCP. Additionally, Acharya, Schnabl and Suarez (2012) show that banks with greater reliance on ABCP financing experienced significant losses during the financial crisis due to explicit guarantees on the conduits to investors.

Large banks exposed to the ABCP markets were associated with relatively sharper reductions in outstanding loans amounts and originations to small businesses, compared to small banks and large banks without ABCP exposure. Panel A of Table 8 reports the annual growth rates on the outstanding amounts of small business loans from the Call Reports for June 2006 - June 2007, June 2007 - June 2008 and June 2008 - June 2009 periods.[28] Small business loans are alternatively defined as loans up to $1 million, which is commonly associated with small business lending in the literature, and loans up to $250K, the latter presumably being the most comparable to the SBET survey firms. The calculations are shown for three sets of banks based upon exposure to the ABCP market just before the initial collapse of the ABCP markets: small banks; large banks whose bank holding company (BHC) with ABCP exposure measured as of June 2007; and large banks whose BHC without ABCP exposure measured as of June 2007. We only include banks with values in the previous year for each calculation. The outstanding amount of small business loans increased at all three bank groups in 2006-2007 and 2007-2008, but declined in 2008-2009. The decrease is generally the largest for large banks with ABCP exposure, and the effect being most pronounced for small business loans up to $250 thousand.

Panel B of Table 8 reports the annual growth rates on the small business loan originations from the Community Reinvestment Act (CRA) dataset for the December 2006 - December 2007, December 2007 - December 2008 and December 2008 - December 2009 periods for only large banking institutions, given that only large institutions are required to report the data.[29] The results are displayed for all small business loans under $1 million, and all small business loan to businesses with annual revenue under $1 million and loan amounts under $1 million. Information for loans to businesses with annual revenue under $1 million are not available by loan size breakdowns in the data. The latter is the most comparable to the SBET survey firms. We only

[28] Specifically, we consider commercial and industrial loans up to $1 million. June is the only dates for which the Call Reports contain these data.

[29] Only data as of the end of the year is available. We are able to match approximately 80%-90% of large banks in the Call Report dataset to the CRA dataset. Data for small banks are not used, given that only 5% are able to be matched. This is not surprising given that only larger banks are included in the CRA dataset.

include banks with values in the previous year for each calculation. Small business loan originations increased both large banks in 2006-2007, but declined in 2007-2008 and 2008-2009. The sharpest decrease comes in the 2008-2009 period, and is most pronounced for large banks with ABCP exposure. These patterns are more pronounced for loans to small businesses with annual revenues under $1 million.

Evidence from the existing literature also shows that large banks with ABCP exposure cut lending more sharply following the Lehman Brothers collapse.[30] The results from Table 8 suggest that large banks began curtailing small business lending soon after the start of the financial crisis in 2007. While outstanding loan amounts actually grew in the 2007-2008 period, originations sharply fell. One possible explanation why outstanding loan amounts increased in 2008 may be that small businesses with credit lines began drawing down credit lines during that period. These findings are consistent with those in Ivashina and Scharfstein (2010) for larger firms, who show that reduced bank funding shocks due to disruptions in the short-term debt markets following the Lehman Brothers collapse contributed to reductions in lending.

Consistently, propensities to report financial constraints amongst non-regular borrowers appear to sharply increase much sooner than for regular borrowers in Figure 1. The figure reports the sample mean for *NotSatisfied* for each period, over the same time periods by borrower type in Figure 1: regular (solid trend) and non-regular (dotted trend) borrowers. The light grey region denotes the time period beginning with the initial collapse of the ABCP markets in 2007:Q3, and

[30] Chodorow-Reich (2014) shows that relatively larger borrowers associated with lenders that were the most adversely affected by the crisis experienced greater difficulty in obtaining new loans and faced higher loan costs. Ivashina and Scharfstein (2010) document large declines in aggregate lending following the Lehman Brothers collapse, and attribute them to bank funding shocks related to short-term financing. Acharya and Mora (2015) show that banks with greater exposure to the ABCP markets reduced lending overall, particularly those with greater undrawn commitments on existing credit lines to firms. Focusing on small business loans, Greenstone, Mas and Nguyen (2014) finds sharper declines in originations during the crisis period in banks that presumably experienced greater funding liquidity shocks during the crisis period.

the dark grey region denotes the time period beginning with the collapse of Lehman Brothers in 2008:Q3. Beginning in 2007:Q4, the proportion of firms reporting financial constraints begins to increase, and the gap between non-regular and regular borrowers seems to widen. After the collapse of Lehman Brothers, the trend sharply increases for both types of borrowers. Because regular borrowers are more likely to hold credit lines than non-regular borrowers, these results suggest that credit lines provided liquidity to these firms. However, the sharp increase in financial constraints after the Lehman Collapse suggest that these borrowers may have encountered difficulties in rolling over debt positions.

4.1. Empirical Design

We construct tests that exploit credit supply shocks from large banks exposed to the ABCP markets prior to the crisis, which likely are independent of other factors related to credit demand during the crisis. Small business customers of exposed banks may not be able to perfectly substitute reductions in the supply of credit with financing from other banks, and so may be more likely to report financial constraints. Because banks exposed to the ABCP markets are generally large and geographically diversified, we are able to construct regional measures of ABCP market exposure to answer the following question: Were borrowers in the affected regions better able to substitute bank financing sources if they had better access to small banks relative to other, large banks without ABCP exposure? That is, did accessibility to small bank finance improve ability in these firms to satisfy borrowing needs?

We develop our predictions on the *change* in the impact of small bank accessibility on firm financial constraints for regions with and without ABCP exposure. To facilitate the relevant comparison, *SmallBankShare* is redefined to only include banks without ABCP exposure before the crisis; otherwise, its sensitivity to *NotSatisfied* would represent comparative advantages of small banks relative to both large banks with and without ABCP exposure. If small banks are better able to cater to small businesses experiencing reductions in credit supply due to their lender's exposure to the ABCP market disruptions, then small bank comparative advantages should increase for firms in the affected regions while it should not in other regions.[31]

To obtain test these predictions, the use following OLS regression model:

$$\begin{aligned} NotSatisfied_{i,t} = {} & \alpha + \beta_1\, SmallBankShare_{NonABCP,i} \\ & + \beta_2\, ABCPExposure_i^{\phi,07:Q2} \\ & + \beta_3\, SmallBankShare_{NonABCP,i} \times ABCPExposure_i^{\phi,07:Q2} \\ & + \beta_4\, D_t^{[dt1,dt2]} \times SmallBankShare_{NonABCP,i} \\ & + \beta_5\, D_t^{[dt1,dt2]} \times ABCPExposure_i^{\phi,07:Q2} \\ & + \beta_6\, D_t^{[dt1,dt2]} \times SmallBankShare_{NonABCP,i} \times ABCPExposure_i^{\phi,07:Q2} \\ & + \mathbf{X_{i,t}} + \tau_t + \varepsilon_{i,t} \end{aligned}$$

We restrict the sample period to be from 2006:M8 (i.e., one year prior to the initial collapse in the ABCP markets) through 2010:M2 (i.e., when the Asset-Backed Commercial Paper Money Market Mutual Fund Liquidity Facility (AMLF) operations were ended). For firm *i*, $SmallBankShare_{i,NonABCP}$ is the proportion of small bank branches within a 50 km radius of the firm relative to all bank branches without exposure to the ABCP markets. Local ABCP exposure is measured as the average ABCP exposure relative to bank equity on the bank holding company-level of all banks within a 50 km radius of the firm, weighted by the number of branches.[32] $ABCPExposure_i^{\phi,07:Q2}$ is an indicator variable taking value 1 if the local ABCP exposure relative

[31] Implicit in these predictions is the hypothesis that small businesses cannot perfectly substitute funding sources. While we cannot directly test this hypothesis due to data limitations, existing studies provide affirmative evidence on small businesses (Greenstone, Mas, and Nguyen, 2014). Additionally, we are able to indirectly test this hypothesis by estimating the change in the impact of a firm being located in regions with ABCP exposure during the crisis period, and find affirmative evidence.

[32] The total dollar ABCP exposure of a bank holding company is measured using definitions from Boyson, Fahlenbrach, and Stulz (2014), using fields obtained from FR Y-9C data based upon credit (BHCKB806 and BHCKB807) and liquidity (BHCKB808 and BHCKB809) exposure for conduits sponsored by the bank, bank affiliates, and other institutions. Similar to Acharya, Schnabl, and Suarez (2013), bank holding company-level ABCP exposure is scaled by equity capital, though the results are similar using risk-weighted assets.

to other regions is above the ϕ^{th} sample percentile, and 0 otherwise.[33] $D_t^{[dt1,dt2]}$ is an indicator variable taking value 1 between dates *dt1* and *dt2*, and 0 otherwise. In separate model specifications, we use the period associated with the initial disruptions in the ABCP markets until the Lehman Brothers collapse (i.e. *dt1* = 2007:M8, *dt2* = 2008:M9), and the period after the Lehman Brothers collapse to the end of the AMLF operations (i.e. *dt1* = 2008:M10, *dt2* = 2010:M2). The set of control variables, **X**, includes the baseline regression model control variables. Additionally, we also include county unemployment rates and the natural log of the per-capital county wage to control for changes in local economic conditions during the sample period.

We base the tests upon β_6, or this coefficient on the triple interaction term, which is predicted to be negative. The coefficient represents the differences in the change in the small bank comparative advantage between regions with and without ABCP exposure. The model specification allows us to control for differences in regional conditions associated with relatively higher or lower accessibility to small banks regardless of ABCP exposure, and differences in credit demand due to ABCP exposure. Additionally, we estimate the models using $SmallBankShare_{NonABCP}$ measured as of 2007:Q2 to assess whether the results are affected by time variation in local banking market composition, which may be due to other factors related to economic conditions during this time period.

4.2. Results

Before presenting the results, we consider tests on whether there are any differential characteristics in regions with greater and lower $SmallBankShare_{NonABCP}$ differs across ABCP and no ABCP exposure before the crisis period, or in the 2006:M8 to 2007:M7 sample period. One concern is

[33] The results are similar when using instead the proportion of branches with any exposure to the ABCP markets.

that the estimates may be driven by differential trends related to firm and local economic conditions before the crisis. Table 9 estimates regression models using these factors as the dependent variables, and $SmallBankShare_{NonABCP}$, $ABCPExposure^{Any,07:Q2}$, and $SmallBankShare_{NonABCP} \times ABCPExposure^{Any,07:Q2}$ as the explanatory variables, where $ABCPExposure^{Any,07:Q2}$ is based upon whether the region has any exposure to the ABCP markets (i.e., ϕ = 0%). Across all the specifications, the interaction term coefficients are statistically insignificant at the 10% level.

Table 10 presents the results. Panel A displays the estimates using $SmallBankShare_{NonABCP}$, while Panel B displays the estimates using $SmallBankShare_{NonABCP}$ measured as of 2007:Q2, or $SmallBankShare_{NonABCP}^{07:Q2}$. For each panel, separate models display the estimates where D_t is associated with the period after the initial disruptions in the ABCP markets but prior the Lehman Brothers collapse, and after the Lehman Brothers collapse up until the closure of the AMLF operations.[34] Each column reports specifications that vary according to the rank criterion used to calculate $ABCPExposure^{\phi,07:Q2}$: Columns (1) and (4) use any exposure to the ABCP markets (Any), columns (2) and (5) use the 10^{th} sample percentile (> 10^{th}), and columns (3) and (6) use the 25^{th} sample percentile (> 25^{th}). The control variables are included in all the models, but are not reported to conserve space.

The results suggest show that the triple interaction term is negative and statistically significant following the Lehman Brothers failure, while it is insignificant in the period prior to the Lehman Brother failure but after the initial collapse in the ABCP markets. The results are similar across Panels A and B, suggesting that changes in local small bank share during the crisis period is not driving the results. The results show that the comparative advantage of small banks

[34] The results are similar when including both sets of interaction terms related to the different crisis periods. The table reports the results for each individual set for viewing convenience.

increases more in regions with ABCP exposure relative to those without. The estimates are also economically significant. A one standard deviation increase in $SmallBankShare^{NonABCP,07:Q2}$ represents a change in the marginal effects of 4.65% in the regions with relative to without exposure, which represents approximately to 21% of the sample mean in the period following the Lehman Brothers failure.

Additionally, small bank comparative advantages do not change significantly in regions without ABCP exposure, given that the coefficient on $D^{[08:M10,10:M2]} \times SmallBankShare_{NonABCP}^{07:Q2}$ is statistically insignificant. The results also confirm that borrowers in the exposed regions face significant switching costs, as the $D^{[08:M10,10:M2]} \times ABCPExposure^{\phi,07:Q2}$ coefficient is positive and significant in most of the specifications. Finally, ABCP exposure increases *NotSatisfied*, and the effects are non-linear. The results are strongest for any ABCP exposure, and attenuate as the criterion threshold is increased.

When examining the estimates by borrower type in Table 11, we find that the effects are large and significant for non-regular borrowers, and insignificant for regular borrowers. The table only reports the specifications for after the Lehman Brothers failure and defining the $ABCPExposure^{07:Q2}$ as any exposure. The triple interaction coefficient is negative and statistically significant for both of the non-regular borrower specifications, and is substantially larger than those for the regular borrower specifications. Additionally, the effect of ABCP exposure is also much larger on non-regular than regular borrowers.

These results are consistent with evidence from Ivashina and Scharfstein (2010) and Campello et al. (2010), who show that firms relied heavily on credit lines during the financial crisis for liquidity. Regular borrowers are more likely to be associated with credit lines than non-regular borrowers by definition, and so could have drawn on those sources. Additionally, Acharya and

Mora (2015) find evidence that banks were generally able to fulfill lending commitments during this period, which is also consistent with the insignificance of the triple interaction term for the regular borrower subsample. The results suggest that non-regular borrowers experienced relatively higher financial constraints, and that small bank comparative advantages were the largest for these borrowers.

5. Conclusions

This paper addresses how small bank ability to provide liquidity to their borrowers across normal and distressed economic periods has changed over time, particularly during the recent financial crisis. Our dataset, which includes information gathered from the Small Business Economic Trends (SBET) survey, allows us to measure financial constraints from the perspective of the small businesses, and has a number of advantages over other datasets used in the literature. We show that small bank comparative advantages remained stable over time, and that small banks maintain their role as liquidity providers following local economic shocks.

We also examine how these comparative advantages may have changed during the recent financial crisis. Exploiting local variation in exposure to disruptions in the ABCP markets following the Lehman Brothers failure in September 2008, we provide evidence that some small businesses facing reductions in credit availability from banks dependent on the ABCP markets could not perfectly substitute bank financing sources. However, accessibility to small bank finance alleviated these effects, particularly in borrowers that may not have had access to lines of credit to draw upon during this period.

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Table 1: Variable Descriptions and Summary Statistics

The analyses use firm-level data from the Small Business Economic Trends (SBET) survey, available on a monthly basis from 1993:M6 – 2012:M12. These data are augmented with data from several other sources: Summary of Deposits (SoD) data available annually in June, annual Census Bureau (Census) data, quarterly bank Call Reports, monthly and quarterly Federal Reserve Economic Data (FRED) data, and quarterly Bureau of Labor Statistics (BLS) data. The data related to the explanatory variables are merged using their most recent values if not available monthly. Panel A briefly describes the regression variables and gives the data sources. Panel B displays summary statistics of all the variables based upon the data sample for which *NotSatisfied* is available. Sample percentiles and standard deviations are not displayed for binary variables because they follow trivially from the means.

Panel A: Variable Descriptions

Variable	Description	Source
Key Dependent Variable:		
NotSatisfied	Binary variable of whether the firm did not satisfy borrowing needs in the past 3 months for all firms that financing within the previous three months	SBET
NotSatisfied (Regular)	Binary variable of whether the firm did not satisfy borrowing needs in the past 3 months for firms that seek financing at least once every three months	SBET
NotSatisfied (Non-Regular)	Binary variable of whether the firm did not satisfy borrowing needs in the past 3 months for firms that do not seek financing at least once every three months	SBET
Alternative Dependent Variables:		
ExpectedDifficulty	Binary variable of whether it will be harder for firm to get financing in next 3 months (Available only for regular borrowers)	
LoanSpread	Interest rate paid by the firm on debt financing minus 3-month Treasury Bill yield for loan maturities less than or equal to one year for loans originated within the past three months (Available for a subset of regular and non-regular borrowers)	SBET
RateChange	The change in the loan interest rate in the current period versus the previous quarter based on a five-point scale (MUCH HIGHER = 2, MUCH LOWER = -2) (Available only for regular borrowers)	SBET
Key Explanatory Variable:		
SmallBankShare	Proportion of small bank branches to total bank branches within 50 km of firm	SoD
Control Variables:		
<u>Other Local Bank, Market Characteristics</u>		
EqRat	Average equity ratio (Total Equity to gross total assets (GTA, total assets plus allowances for loan and lease losses and the allocated risk transfer) of banks within 50 km of the firm	Call Reports, SoD
IlliquidityRat	Average liquidity creation ratio (CATFAT to GTA) for banks to within 50 km of the firm	Call Reports, SoD
DepositHHI	The Herfindahl-Hirschman Index (HHI) based upon branch deposits within 50 km of the firm	SoD
Branch/Pop	The number of bank branches within 50 km of the firm divided by population based upon year 2000 zip-code-level population	SoD, Census

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FewBanks	Indicator variable that takes a value of one if the number of banks within 50 km of the firm is below the 10th sample percentile for a particular date, and zero otherwise.	SoD
Metro	Indicator variable that takes a value of one if the firm is located in a metropolitan statistical area (MSA) or New England county metropolitan area (NECMA), and zero otherwise.	
CountyPop	Population size of the county of the firm's location	Census
Firm Characteristics		
ln(Sales)	Natural log of one plus the lower bound of sales in thousands in each sales category in the last quarter. Sales Categories: 0='NO REPLY' 1='UNDER $12.5K' 2='$12.5K - 24.9K' 3='$25K - $49.9K' 4='$50K - $87.49K' 5='$87.5K - $199.9K' 6='$200K - $374.9K' 7='$375K - $749.9K' 8='$750K - $1,249.9K' 9='$1,250K OR MORE'	SBET
ln(Employees)	Natural log of one plus the lower bound of the number of employees in each employee category in the last quarter. Employee Categories: 0='NO REPLY' 1='ONE' 2='TWO' 3='3 - 5' 4='6 - 9' 5='10 - 14' 6='15 - 19' 7='20 - 39' 8='40 OR MORE'	SBET
Corporation	Indicator variable that takes a value of one if the firm is incorporated as a corporation, and zero otherwise.	SBET
Partnership	Indicator variable that takes a value of one if the firm is incorporated as a partnership, and zero otherwise.	SBET
Proprietorship	Indicator variable that takes a value of one if the firm is a proprietorship or other, and zero otherwise. (Omitted from the regressions to avoid perfect collinearity.)	SBET
ExpGenCond	The expected change in general conditions over the next 6 months versus the current period based on a five-point scale (MUCH BETTER = 2, MUCH WORSE = -2)	SBET
ExpSales	The expected change in gross sales in the next quarter versus the current period based on a five-point scale (MUCH HIGHER = 2, MUCH LOWER = -2)	SBET
ChSales	The change in gross sales in the current period versus the prior quarter based on a five-point scale (MUCH HIGHER = 2, MUCH LOWER = -2)	SBET
Other Factors		
FedFundsRate	The Federal Funds rate at the end of each month	FRED
$Unemployment_{County}$	Unemployment rate of the county of the firm's location	BLS
$Unemployment_{National}$	Unemployment rate on the national level	FRED
$Wage_{County}$	Per-capita total wages of the county of the firm's location	BLS
$Wage_{National}$	Per-capita total wages on the national level	BLS

Panel B: Summary Statistics						
	N	Mean	StDev	25th Pct.	Median	75th Pct.
Dependent Variables:						
NotSatisfied	77855	0.155				
NotSatisfied (Regular)	56245	0.128				
NotSatisfied (Non-Regular)	21610	0.224				
Alternative Dependent Variables:						
ExpectedDifficulty	51624	0.279				
LoanSpread	45166	5.038	2.227	3.860	4.700	5.710
RateChange	54723	0.129	0.752	0.000	0.000	1.000
Key Explanatory Variable:						
SmallBankShare	77855	0.427	0.249	0.220	0.386	0.592
Control Variables:						
Other Local Bank, Market Characteristics						
EqRat	77855	0.096	0.012	0.088	0.095	0.103
IlliquidityRat	77855	0.421	0.411	0.321	0.383	0.440
DepositHHI	77855	0.147	0.091	0.089	0.129	0.178
Branch/Pop	77855	0.001	0.002	0.000	0.001	0.002
FewBanks	77855	0.103				
Metro	77855	0.529				
CountyPop (thou)	77855	520	1154	48	164	500
Firm Characteristics						
Sales ($thou.)	75660	328.987	415.375	50.000	87.500	375.000
Employees	77253	11.278	12.019	3.000	6.000	15.000
Corporation	77855	0.694				
Partnership	77855	0.059				
ExpGenCond	77855	0.029	0.772	0.000	0.000	0.000
ExpSales	77855	0.170	1.002	-1.000	0.000	1.000
ChSales	77855	-0.023	0.909	-1.000	0.000	1.000
Other Factors						
FedFundsRate	77904	3.110%	2.266%	0.390%	3.260%	5.260%
$Wage_{County}$ *($thou)*	77855	26.473	16.582	14.640	22.829	34.521
$Wage_{National}$ *($thou)*	77855	29.402	9.004	20.864	28.356	37.478
$Unemployment_{County}$	76985	5.871%	2.707%	3.900%	5.300%	7.200%
$Unemployment_{National}$	77855	6.099%	1.800%	4.700%	5.600%	7.000%

Table 2: Baseline Regression Models

This table presents results from OLS regression models in which the dependent variable is *NotSatisfied* for all borrowers (Panel A) and by borrower type (Panel B). *NotSatisfied* is a binary variable coded 1 if the firm reports that it did not satisfy its borrowing needs and 0 otherwise. The key explanatory variable is *SmallBankShare*, defined as the proportion of bank branches within a 50 kilometer radius of the firm that belong to small banks. All borrowers refer to firms that sought or obtained debt financing within the past three months. Regular borrowers refer to firm who also seek debt financing at least once every three months, while those that do not are referred to as non-regular borrowers. Control variables related to other bank and market characteristics include *EqRat*, *IlliquidityRat*, *DepositHHI*, *Branch/Pop*, *FewBanks*, *Metro*, and *ln(CountyPop)*. Control variables related to firm characteristics include *ln(Sales)*, *ln(Employees)*, *Corporation*, *Partnership*, *ExpGenCond*, *ExpSales*, *ChSales*, and industry fixed effects. All variables are defined in Table 1. Fixed effects on year-month and/or state are also included in the models where indicated, but not reported. Robust standard errors clustered at the 3-digit ZIP code and year-month levels are used to calculate the t-statistics, which are displayed in parentheses. Statistical significance is denoted as ***, **, and * for 1%, 5%, and 10% levels, respectively.

Panel A: All Borrowers					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
Borrower Subsample:	All	All	All	All	All
Dependent Variable:	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*
SmallBankShare	-0.105***	-0.090***	-0.118***	-0.085***	-0.071***
	(-11.42)	(-9.28)	(-13.51)	(-9.02)	(-5.75)
Other Local Bank, Market Characteristics					
EqRat		0.394**		0.305	1.169***
		(1.97)		(1.59)	(5.13)
IlliquidityRat		0.000		0.002	-0.009**
		(-0.04)		(0.39)	(-2.28)
DepositHHI		0.941		1.251	1.534**
		(1.01)		(1.56)	(2.08)
Branch/Pop		-0.025		-0.005	-0.037
		(-1.15)		(-0.25)	(-1.62)
FewBanks		0.030***		0.022***	0.010
		(3.88)		(3.03)	(1.34)
Metro		-0.002		0.003	-0.003
		(-0.35)		(0.60)	(-0.58)
ln(CountyPop)		0.010***		0.012***	0.013***
		(4.35)		(5.64)	(6.14)
Firm Characteristics					
ln(Sales)			-0.023***	-0.023***	-0.023***
			(-24.52)	(-24.64)	(-24.94)
ln(Employees)			-0.024***	-0.024***	-0.026***
			(-13.95)	(-13.88)	(-13.71)
Corporation			0.007*	0.006	0.009**
			(1.73)	(1.38)	(2.12)
Partnership			0.003	0.003	0.006
			(0.59)	(0.49)	(0.96)
ExpGenCond			-0.020***	-0.020***	-0.021***
			(-9.46)	(-9.51)	(-9.79)
ExpSales			0.002	0.002	-0.002
			(1.16)	(0.97)	(-0.97)
ChSales			-0.026***	-0.026***	-0.028***
			(-15.43)	(-15.52)	(-15.41)
Industry FEs	YES	YES	YES	YES	YES
Year-Month FEs	YES	YES	YES	YES	NO
State FEs	NO	NO	NO	NO	YES
N	77855	77855	77843	77843	77843
Adjusted R^2	1.88%	2.00%	6.53%	6.69%	6.01%

Panel B: By Borrower Types

	(1)	(2)	(3)	(4)
Borrower Subsample:	Regular	Non-Regular	Regular	Non-Regular
Dependent Variable:	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*
SmallBankShare	-0.057***	-0.148***	-0.054***	-0.116***
	(-6.21)	(-8.18)	(-4.68)	(-5.13)
Other Local Bank, Market Characteristics				
EqRat	0.156	0.423	0.995***	1.500***
	(0.82)	(1.15)	(5.10)	(3.98)
IlliquidityRat	-0.003	0.013	-0.010***	-0.007
	(-0.93)	(1.63)	(-3.45)	(-0.90)
DepositHHI	1.089	1.624	1.178	2.027
	(1.31)	(0.91)	(1.50)	(1.12)
Branch/Pop	-0.010	-0.005	-0.045**	-0.015
	(-0.50)	(-0.13)	(-2.27)	(-0.32)
FewBanks	0.024***	0.019	0.016**	-0.006
	(3.68)	(1.37)	(2.19)	(-0.45)
Metro	0.001	0.010	-0.003	-0.002
	(0.13)	(1.00)	(-0.62)	(-0.19)
ln(CountyPop)	0.009***	0.020***	0.009***	0.021***
	(4.50)	(5.15)	(4.54)	(5.16)
Firm Characteristics				
ln(Sales)	-0.018***	-0.029***	-0.018***	-0.030***
	(-17.79)	(-16.55)	(-17.58)	(-16.23)
ln(Employees)	-0.016***	-0.044***	-0.017***	-0.045***
	(-8.15)	(-11.82)	(-8.56)	(-11.65)
Corporation	0.004	0.008	0.007	0.013*
	(0.94)	(1.07)	(1.54)	(1.89)
Partnership	-0.003	0.013	-0.001	0.018
	(-0.42)	(0.98)	(-0.13)	(1.42)
ExpGenCond	-0.021***	-0.018***	-0.021***	-0.021***
	(-9.27)	(-4.09)	(-8.91)	(-5.22)
ExpSales	0.001	0.002	-0.002	-0.002
	(0.59)	(0.58)	(-1.05)	(-0.59)
ChSales	-0.024***	-0.032***	-0.027***	-0.035***
	(-13.75)	(-9.99)	(-14.78)	(-10.24)
Industry FEs	YES	YES	YES	YES
Year-Month FEs	YES	YES	NO	NO
State FEs	NO	NO	YES	YES
N	56235	21608	56235	21608
Adjusted R^2	4.85%	9.55%	4.32%	8.75%

Table 3: Heckman Correction-Adjusted Estimates

This table presents results from second-stage OLS models using a Heckman correction by survey respondent types. Baseline model control variables used in Table 2 are included, although not reported. The inverse Mills ratio is estimated from first-stage probit regression models of whether the dependent variable is non-missing over the entire sample of respondent firms (*InverseMillsRatio1*) and whether a firm is a regular borrower amongst the subsample of borrower firms (*InverseMillsRatio2*). The probit regressions include all control variables from the second-stage regression, while excluding *SmallBankShare*. The probit results are not reported for brevity. Robust standard errors clustered at the 3-digit ZIP code and year-month levels are used to calculate the t-statistics, which are displayed in parentheses. Statistical significance is denoted as ***, **, and * for 1%, 5%, and 10% levels, respectively.

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Borrower Subsample:	All	Regular	Non-Regular	All	Regular	Non-Regular
Dependent Variable:	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*
SmallBankShare	-0.085***	-0.056***	-0.148***	-0.071***	-0.054***	-0.115***
	(-9.07)	(-6.18)	(-8.17)	(-5.73)	(-4.65)	(-5.10)
Heckman Correction Terms						
InverseMillsRatio1	-0.985***	-0.772***	-1.196***	-0.818***	-0.697***	-1.356***
	(-10.74)	(-5.57)	(-4.96)	(-8.76)	(-4.83)	(-4.66)
InverseMillsRatio2		-0.001	-0.633**		-0.150	-1.239***
		(-0.01)	(-2.02)		(-0.85)	(-3.48)
Baseline Model Control Variables	YES	YES	YES	YES	YES	YES
Year-month FEs	YES	YES	YES	NO	NO	NO
State FEs	NO	NO	NO	YES	YES	YES
N	6.86%	4.97%	9.65%	6.13%	4.40%	8.86%
Adjusted R^2	77843	56235	21608	77843	56235	21608

Table 4: Alternative Financial Constraint Measures

This table presents results from OLS regression models in which the dependent variables are alternative financial constraint measures, which are available for a subset of the borrowing firms: *ExpectedDifficulty*, *LoanSpread*, and *RateChange*. The results are reported with and without Heckman correction terms. *InverseMillsRatio1* is calculated separately for the *ExpectedDifficulty*, *LoanSpread* and *RateChange* models based upon the availability of each dependent variable in the first-stage regression model. *InverseMillsRatio2* is calculated based upon whether a firm is a regular borrower amongst the subsample of borrower firms. The first-stage probit regressions include all control variables from the OLS regressions, while excluding *SmallBankShare*. The probit results are not reported for brevity. All variables are defined in Table 1. All the baseline control variables of Table 2 are included, although not reported. All specifications include year-month fixed effects, and none include state fixed effects given that some of the dependent variables are based upon loan price terms. Robust standard errors clustered at the 3-digit ZIP code and year-month levels are used to calculate the t-statistics, which are displayed in parentheses. Statistical significance is denoted as ***, **, and * for 1%, 5%, and 10% levels, respectively.

Dependent Variable:	*(1) Expected Difficulty*	*(2) Expected Difficulty*	*(3) Loan Spread*	*(4) Loan Spread*	*(5) Rate Change*	*(6) Rate Change*
SmallBankShare	-0.105***	-0.104***	-0.252***	-0.252***	-0.063***	-0.062***
	(-7.68)	(-7.65)	(-3.09)	(-3.14)	(-3.89)	(-3.84)
Heckman Correction Terms						
InverseMillsRatio1		0.863***		6.833***		1.531***
		(4.91)		(6.47)		(3.59)
InverseMillsRatio2		-0.618**		-1.196		-0.661
		(-2.13)		(-0.73)		(-0.95)
Baseline Model Control Variables	YES	YES	YES	YES	YES	YES
Year-month FEs	YES	YES	YES	YES	YES	YES
State FEs	NO	NO	NO	NO	NO	NO
N	58739	58739	48786	48786	63151	63151
Adjusted R^2	11.63%	11.68%	16.26%	16.61%	28.35%	28.43%

Table 5: Local Economic Conditions and Comparative Advantages

This table presents results from OLS regression models that include *SmallBankShare* interaction terms with local economic factors. The two measures of local economic conditions include the county-level unemployment rate and the natural log of one plus the per-capita wage of the county of the firm's location. The models also control for bank funding factors and their interaction terms with *SmallBankShare*, which include average, local bank equity ratios and the Federal Funds rate. All variables are defined in Table 1. Continuous variables are mean-centered prior to calculating interaction terms to minimize the influence of multicollinearity (Wooldridge, 2010). All the baseline model control variables of Table 2 are included, although not reported. Robust standard errors clustered at the 3-digit ZIP code and year-month levels are used to calculate the t-statistics, which are displayed in parentheses. Statistical significance is denoted as ***, **, and * for 1%, 5%, and 10% levels, respectively.

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Borrower Subsample:	All	Regular	Non-Regular	All	Regular	Non-Regular
Dependent Variable:	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*
SmallBankShare	-0.070***	-0.044***	-0.131***	-0.026**	-0.018*	-0.054**
	(-7.34)	(-4.67)	(-7.12)	(-2.32)	(-1.65)	(-2.44)
Local Economic Condition						
Unemployment$_{County}$	0.469***	0.381***	0.691***	0.849***	0.684***	1.206***
	(5.02)	(3.95)	(4.46)	(9.09)	(7.45)	(7.30)
SmallBankShare	-1.003***	-0.864***	-1.185**	-1.564***	-1.313***	-1.855***
x Unemployment$_{County}$	(-3.35)	(-2.75)	(-2.35)	(-4.98)	(-3.99)	(-3.60)
Wage$_{County}$	-0.015***	-0.013***	-0.017***	-0.008**	-0.004	-0.014**
	(-3.36)	(-2.77)	(-2.62)	(-2.45)	(-1.12)	(-2.37)
SmallBankShare x Wage$_{County}$	0.041***	0.030***	0.058**	0.034***	0.020*	0.057**
	(3.61)	(2.71)	(2.39)	(2.98)	(1.75)	(2.43)
Bank Funding						
FedFundsRate				-0.009***	-0.007***	-0.012***
				(-8.48)	(-6.96)	(-6.74)
SmallBankShare x FedFundsRate	0.012***	0.010***	0.018**	0.010***	0.008**	0.014**
	(3.54)	(2.74)	(2.42)	(2.87)	(2.12)	(1.98)
EqRat	0.116	-0.024	0.226	0.029	0.040	-0.074
	(0.62)	(-0.13)	(0.60)	(0.18)	(0.25)	(-0.22)
SmallBankShare x EqRat	-0.248	-0.473	0.642	0.360	0.133	1.171
	(-0.43)	(-0.79)	(0.50)	(0.64)	(0.22)	(1.04)
Baseline Model Control Variables	YES	YES	YES	YES	YES	YES
Year-month FEs	YES	YES	YES	NO	NO	NO
State FEs	NO	NO	NO	YES	YES	YES
N	76973	55634	21339	76973	55634	21339
Adjusted R^2	6.90%	5.02%	9.78%	6.95%	5.03%	10.07%

Table 6: Local versus National Economic Conditions

This table presents results from OLS regression models that include *SmallBankShare* interaction terms with local and national economic factors. The two measures of national economic conditions include the nationwide unemployment rate and the natural log of one plus the per-capita wage. All variables are defined in Table 1. Continuous variables are mean-centered prior to calculating interaction terms to minimize the influence of multicollinearity (Wooldridge, 2010). All variables from Table 5 are also included, though the control variables are not reported. Robust standard errors clustered at the 3-digit ZIP code and year-month levels are used to calculate the t-statistics, which are displayed in parentheses. Statistical significance is denoted as ***, **, and * for 1%, 5%, and 10% levels, respectively.

	(1)	*(2)*	*(3)*	*(4)*
Borrower Subsample:	All	All	All	All
Dependent Variable:	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*
SmallBankShare	-0.085***	-0.069***	-0.036***	-0.030***
	(-9.29)	(-7.35)	(-3.12)	(-2.56)
Local Economic Condition				
$Unemployment_{County}$		0.429***		0.430***
		(4.58)		(5.09)
SmallBankShare x $Unemployment_{County}$		-0.556*		-0.686**
		(-1.81)		(-2.28)
$Wage_{County}$		-0.015***		-0.007**
		(-3.30)		(-2.14)
SmallBankShare x $Wage_{County}$		0.034***		0.032**
		(2.58)		(2.53)
National Economic Condition				
$Unemployment_{National}$			2.155***	1.779***
			(12.19)	(9.89)
SmallBankShare x $Unemployment_{National}$	-4.201***	-3.521***	-4.454***	-3.622***
	(-7.06)	(-5.61)	(-7.35)	(-5.93)
$Wage_{National}$			-0.009	-0.005
			(-1.16)	(-0.71)
SmallBankShare x $Wage_{National}$	0.048**	0.023	0.022	0.004
	(2.49)	(0.90)	(1.18)	(0.20)
Baseline Model Control Variables	YES	YES	YES	YES
Bank Funding Interaction Terms	YES	YES	YES	YES
Year-month FEs	YES	YES	NO	NO
State FEs	NO	NO	YES	YES
N	77843	76973	77843	76973
Adjusted R^2	6.84%	6.95%	7.13%	7.18%

Table 7: Time Trends in Comparative Advantages

This table presents results from OLS regression models that include *SmallBankShare* interaction terms with a time trend. The trend variable based upon the number of months (divided by 12) since the beginning of the sample period (*Trend*). Continuous variables are mean-centered prior to calculating interaction terms to minimize the influence of multicollinearity (Wooldridge, 2010). Interaction terms with local economic factors are also included where indicated. Other variables from Table 6 are also included, though the control variables are not reported. Robust standard errors clustered at the 3-digit ZIP code and year-month levels are used to calculate the t-statistics, which are displayed in parentheses. Statistical significance is denoted as ***, **, and * for 1%, 5%, and 10% levels, respectively.

	(1)	*(2)*	*(3)*	*(4)*
Borrower Subsample:	All	All	All	All
Dependent Variable:	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*
SmallBankShare	-0.069***	-0.066***	-0.028**	-0.025**
	(-7.32)	(-6.39)	(-2.38)	(-2.09)
Local Economic Proxies				
Unemployment$_{County}$	0.429***	0.405***	0.452***	0.440***
	(4.58)	(4.09)	(5.27)	(4.89)
SmallBankShare x Unemployment$_{County}$	-0.561*	-0.595*	-0.698**	-0.672**
	(-1.81)	(-1.66)	(-2.31)	(-1.96)
Wage$_{County}$	-0.015***	-0.015***	-0.007**	-0.007**
	(-3.30)	(-3.42)	(-2.11)	(-2.02)
SmallBankShare x Wage$_{County}$	0.034***	0.035***	0.032***	0.033**
	(2.58)	(2.60)	(2.54)	(2.53)
Trend Interaction Terms				
Trend			0.000*	0.000*
			(1.85)	(1.81)
Trend x SmallBankShare	0.000	0.000	0.000	0.000
	(-0.19)	(-0.19)	(-0.38)	(-0.35)
Trend x Unemployment$_{County}$		0.001		0.001
		(0.50)		(1.14)
Trend x SmallBankShare x Unemployment$_{County}$		-0.004		-0.004
		(-1.13)		(-1.22)
Trend x Wage$_{County}$		0.000		0.000
		(0.76)		(0.52)
Trend x SmallBankShare x Wage$_{County}$		0.000		0.000
		(0.02)		(-0.03)
Baseline Model Control Variables	YES	YES	YES	YES
Bank Funding Interaction Terms	YES	YES	YES	YES
National Economic Condition Interaction Terms	YES	YES	YES	YES
Year-month FEs	YES	YES	NO	NO
State FEs	NO	NO	YES	YES
N	76973	76973	76973	76973
Adjusted R^2	6.95%	6.95%	7.19%	7.19%

Table 8: Growth in Outstanding Loans and Originations to Small Businesses Around the Financial Crisis

This table presents growth rates based on the outstanding loan amounts (Panel A) and loan originations (Panel B) to small businesses from 2006-2007, 2007-2008 and 2008-2009. Data for outstanding loan amounts is available from the Call Reports for June of every year. Data for origination amounts is available from the Community Reinvestment Act (CRA) for December of every year, and is only available for large banks (i.e., total assets exceeding $1 billion). The calculations are made for three different bank types for outstanding loan amounts: small banks, large banks whose bank holding company did not use the asset-backed commercial paper markets for financing (No ABCP), and large banks whose bank holding company used the asset-backed commercial paper markets for financing (ABCP) during the calculation period. We only include banks with values in the previous year in the calculations. For outstanding loan amounts, the growth rates reported are for loan amounts up to $1 million (Amount < $1M) and up to $250 thousand (Amount < $250K) for all commercial and industrial loans. For loan originations, the growth rates reported are for loan amounts up to $1 million for all small businesses (All Small Businesses, Amount < $1M) and for only businesses with annual revenues of under $1 million (Business Revenues < $1M, Amount < $1M).

Panel A: Growth in Outstanding Loan Amounts (Call Report)

	All Firms, Outstanding Loans, Amount < $1M			All Firms, Outstanding Loans, Amount < $250K		
Period	Small Bank	Large Bank, No ABCP Exposure	Large Bank, ABCP Exposure	Small Bank	Large Bank, No ABCP Exposure	Large Bank, ABCP Exposure
June 2006 - June 2007	6.80%	11.20%	23.30%	4.30%	11.30%	20.60%
June 2007 - June 2008	4.70%	8.60%	7.80%	1.50%	4.80%	19.90%
June 2008 - June 2009	-2.60%	-2.80%	-4.40%	-4.70%	-3.20%	-6.70%

Panel B: Growth in Loan Origination Amounts (CRA)

	All Small Businesses, Loan Origination, Amount < $1M		Business Revenues < $1M, Loan Origination, Amount < $1M	
Period	Large Bank, No ABCP Exposure	Large Bank, ABCP Exposure	Large Bank, No ABCP Exposure	Large Bank, ABCP Exposure
December 2006 - December 2007	5.10%	20.30%	5.80%	15.00%
December 2007 - December 2008	-6.90%	-18.10%	-10.10%	-28.90%
December 2008 - December 2009	-26.00%	-39.70%	-30.10%	-44.10%

Table 9: Pre-Crisis Trends in Firm and Local Economic Conditions

This table presents results from OLS regression models over the 2006:M8-2007:M7 sample period, in which the dependent variables are *ChSales, ExpSales, ExpGenCond,* county-level *Wage,* and county-level *Unemployment* for all borrowers. $SmallBankShare_{NonABCP}$ is the proportion of small bank branches relative to total bank branches whose bank holding company did not have exposure to the ABCP markets. $ABCPExposure^{Any,07:Q2}$ is a dummy variable taking value 1 if any banks within a 50km radius of the firm had exposure to the ABCP market though its bank holding company as of 2007:Q2, and zero otherwise. Year-month fixed effects are included in all specifications. Robust standard errors clustered at the 3-digit ZIP code level are used to calculate the t-statistics, which are displayed in parentheses. Statistical significance is denoted as ***, **, and * for 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	*ChSales*	*ExpSales*	*ExpGenCond*	*Wage*	*Unemployment*
$SmallBankShare_{NonABCP}$	0.087	0.006	0.143	-0.025	0.001
	(0.55)	(0.03)	(1.09)	(-0.08)	(0.08)
$ABCPExposure^{Any,07:Q2}$	-0.024	0.069	0.112	0.537**	0.008
	(-0.22)	(0.51)	(1.22)	(2.18)	(0.67)
$SmallBankShare_{NonABCP}$	-0.055	-0.074	-0.205	-0.471	-0.009
x $ABCPExposure^{Any,07:Q2}$	(-0.32)	(-0.38)	(-1.44)	(-1.40)	(-0.62)
Year-month FEs	YES	YES	YES	YES	YES
N	4230	4230	4230	4230	4230
Adjusted R^2	0.85%	1.55%	1.03%	5.52%	6.77%

Table 10: Local ABCP Exposure around Crisis Period

This table presents results from OLS regression models over the 2006:M8-2010:M2 sample period, in which the dependent variable is *NotSatisfied* for all borrowers. Panel A reports results using $SmallBankShare_{NonABCP}$ as the key explanatory variable, while Panel B reports the results using values measured as of 2007:Q2, or $SmallBank_{NonABCP}^{07:Q2}$, as the key explanatory variable. $ABCPExposure^{\phi,78:Q2}$ is a dummy variable taking value 1 if the regional ABCP exposure measured as of 2007:Q2 is above the ϕ^{th} sample percentile, and zero otherwise. The criterion include above the 0^{th} percentile, or any exposure (Any); above the 10^{th} percentile (> 10^{th}); and above the 25^{th} percentile (> 25^{th}). Regional ABCP exposure is defined as the average, ratio of ABCP exposure relative to bank equity of banks located within a 50km radius of the firm, weighted by the number of bank branches. The time dummy variables (*D*) take value one for the period corresponding with the crisis period (Pre-Lehman Brothers failure from 2007:M8 to 2008:M9, and Post-Lehman Brothers failure from 2008:M10 to 2010:M2), and zero otherwise. Robust standard errors clustered at the 3-digit ZIP code and year-month levels are used to calculate the t-statistics, which are displayed in parentheses. Statistical significance is denoted as ***, **, and * for 1%, 5%, and 10% levels, respectively.

Panel A: $SmallBankShare_{NonABCP}$

	(1)	(2)	(3)	(4)	(5)	(6)
ABCPExposure Criterion:	Any	> 10^{th}	> 25^{th}	Any	> 10^{th}	> 25^{th}
Dependent Variable:	*Not Satisfied*	*Not Satisfied*	*Not Satisfied*	*Not Satisfied*	*Not Satisfied*	*Not Satisfied*
$SmallBankShare_{NonABCP}$	-0.027	0.053	-0.021	-0.075	0.030	0.004
	(-0.44)	(1.39)	(-0.70)	(-1.42)	(0.83)	(0.13)
$ABCPExposure^{\phi,07:Q2}$	0.025	0.100***	0.044*	-0.035	0.036	0.009
	(0.74)	(3.23)	(1.76)	(-0.93)	(1.55)	(0.39)
$SmallBankShare_{NonABCP}$	-0.040	-0.133***	-0.038	0.083	-0.027	0.004
x $ABCPExposure^{\phi,07:Q2}$	(-0.58)	(-3.10)	(-0.92)	(1.54)	(-0.65)	(0.08)
Crisis Period, Pre-Lehman Brothers Failure (2007:M8-2008:M9)						
$D^{[07:M8,08:M9]}$ x $SmallBankShare_{NonABCP}$	-0.019	-0.052	0.015			
	(-0.17)	(-0.87)	(0.33)			
$D^{[07:M8,08:M9]}$ x $ABCPExposure^{\phi,07:Q2}$	-0.016	-0.080	-0.039			
	(-0.20)	(-1.49)	(-0.99)			
$D^{[07:M8,08:M9]}$ x $SmallBankShare_{NonABCP}$	0.091	0.141*	0.061			
x $ABCPExposure^{\phi,07:Q2}$	(0.79)	(1.92)	(1.06)			
Crisis Period, Post-Lehman Brothers Failure (2008:M10-2010:M2)						
$D^{[08:M10,10:M2]}$ x $SmallBankShare_{NonABCP}$				0.107	0.010	-0.057
				(1.00)	(0.20)	(-1.32)
$D^{[08:M10,10:M2]}$ x $ABCPExposure^{\phi,07:Q2}$				0.138**	0.092**	0.049
				(2.03)	(2.06)	(1.37)
$D^{[08:M10,10:M2]}$ x $SmallBankShare_{NonABCP}$				-0.234**	-0.146**	-0.044
x $ABCPExposure^{\phi,07:Q2}$				(-2.00)	(-2.28)	(-0.75)
Baseline Control Variables	YES	YES	YES	YES	YES	YES
Local Economic Proxies	YES	YES	YES	YES	YES	YES
Year-Month FEs	YES	YES	YES	YES	YES	YES
N	16038	16038	16038	16038	16038	16038
Adjusted R^2	7.67%	7.70%	7.71%	7.75%	7.77%	7.79%

Panel B: *SmallBankShare*$_{NonABCP}$ Measured as of 2007:Q2						
	(1)	(2)	(3)	(4)	(5)	(6)
ABCPExposure Criterion:	Any	> 10th	> 25th	Any	> 10th	> 25th
Dependent Variable:	*Not Satisfied*	*Not Satisfied*	*Not Satisfied*	*Not Satisfied*	*Not Satisfied*	*Not Satisfied*
$SmallBankShare_{NonABCP}^{07:Q2}$	-0.020	0.069	-0.010	-0.077	0.039	0.004
	(-0.32)	(1.64)	(-0.30)	(-1.42)	(0.99)	(0.12)
$ABCPExposure^{\phi,07:Q2}$	0.026	0.109***	0.048*	-0.038	0.041	0.008
	(0.76)	(3.26)	(1.87)	(-0.97)	(1.59)	(0.36)
$SmallBankShare_{NonABCP}^{07:Q2}$ x $ABCPExposure^{\phi,07:Q2}$	-0.040	-0.140***	-0.042	0.087	-0.036	0.005
	(-0.58)	(-3.08)	(-0.98)	(1.56)	(-0.80)	(0.12)
Crisis Period, Pre-Lehman Brothers Failure (2007:M8-2008:M9)						
$D^{[07:M8,08:M9]}$ x $SmallBankShare_{NonABCP}^{07:Q2}$	-0.034	-0.056	0.005			
	(-0.29)	(-0.79)	(0.11)			
$D^{[07:M8,08:M9]}$ x $ABCPExposure^{\phi,07:Q2}$	-0.023	-0.079	-0.042			
	(-0.27)	(-1.29)	(-1.04)			
$D^{[07:M8,08:M9]}$ x $SmallBankShare_{NonABCP}^{07:Q2}$ x $ABCPExposure^{\phi,07:Q2}$	0.100	0.133	0.062			
	(0.82)	(1.60)	(1.04)			
Crisis Period, Post-Lehman Brothers Failure (2008:M10-2010:M2)						
$D^{[08:M10,10:M2]}$ x $SmallBankShare_{NonABCP}^{07:Q2}$				0.115	0.031	-0.032
				(1.11)	(0.57)	(-0.70)
$D^{[08:M10,10:M2]}$ x $ABCPExposure^{\phi,07:Q2}$				0.139**	0.104**	0.064*
				(2.07)	(2.17)	(1.70)
$D^{[08:M10,10:M2]}$ x $SmallBankShare_{NonABCP}^{07:Q2}$ x $ABCPExposure^{\phi,07:Q2}$				-0.230**	-0.151**	-0.064
				(-2.04)	(-2.28)	(-1.05)
Baseline Control Variables	YES	YES	YES	YES	YES	YES
Local Economic Proxies	YES	YES	YES	YES	YES	YES
Year-Month FEs	YES	YES	YES	YES	YES	YES
N	16038	16038	16038	16038	16038	16038
Adjusted R^2	7.66%	7.69%	7.70%	7.73%	7.76%	7.78%

Table 11: Local ABCP Exposure by Borrower Types

This table presents results from OLS regression models over the 2006:M8-2010:M2 sample period, in which the dependent variable is *NotSatisfied* for regular and non-regular borrowers. Specifications using $SmallBankShare_{NonABCP}$ is reported in Columns (1) and (3), and those using $SmallBank_{NonABCP}^{07:Q2}$ is reported in Columns (2) and (4). *ABCPExposure* criterion used for all specifications above the 0th sample percentile (*any* exposure). Robust standard errors clustered at the 3-digit ZIP code and year-month levels are used to calculate the t-statistics, which are displayed in parentheses. Statistical significance is denoted as ***, **, and * for 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Borrower Type:	Regular	Regular	Non-Regular	Non-Regular
ABCPExposure Criterion:	Any	Any	Any	Any
Dependent Variable:	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*
$SmallBankShare_{NonABCP}$	-0.028		-0.317**	
	(-0.36)		(-2.39)	
$SmallBankShare_{NonABCP}^{07:Q2}$		-0.033		-0.310**
		(-0.41)		(-2.12)
$ABCPExposure^{Any,07:Q2}$	-0.001	-0.008	-0.196**	-0.188*
	(-0.02)	(-0.11)	(-2.12)	(-1.80)
$SmallBankShare_{NonABCP}$ x $ABCPExposure^{Any,07:Q2}$	0.025		0.345***	
	(0.32)		(3.15)	
$SmallBankShare_{NonABCP}^{07:Q2}$ x $ABCPExposure^{Any,07:Q2}$		0.035		0.329***
		(0.43)		(2.54)
Crisis Period, Post-Lehman Brothers Failure (2008:M10-2010:M2)				
$D^{[08:M10,10:M2]}$ x $SmallBankShare_{NonABCP}$	0.043		0.407	
	(0.37)		(1.21)	
$D^{[08:M10,10:M2]}$ x $ABCPExposure^{Any,07:Q2}$	0.056		0.417*	
	(0.71)		(1.70)	
$D^{[08:M10,10:M2]}$ x $SmallBankShare_{NonABCP}^{07:Q2}$		0.060		0.372
		(0.52)		(1.15)
$D^{[08:M10,10:M2]}$ x $ABCPExposure^{Any,07:Q2}$		0.066		0.385
		(0.84)		(1.61)
$D^{[07:M8,08:M9]}$ x $SmallBankShare_{NonABCP}$ x $ABCPExposure^{Any,07:Q2}$	-0.122		-0.648*	
	(-1.06)		(-1.86)	
$D^{[08:M10,10:M2]}$ x $SmallBankShare_{NonABCP}^{07:Q2}$ x $ABCPExposure^{Any,07:Q2}$		-0.137		-0.576*
		(-1.20)		(-1.74)
Baseline Control Variables	YES	YES	YES	YES
Local Economic Variables	YES	YES	YES	YES
Year-Month FEs	YES	YES	YES	YES
N	11791	11791	4247	4247
Adjusted R^2	5.69%	5.68%	11.58%	11.49%

Figure 1: Firm Financial Constraints from 2007-2009

This table presents the proportion of firms reporting financial constraints for regular (solid line) and non-regular (dotted line) borrowers from 2007:Q1 through 2009:Q4. The light grey region correspond with the period following the initial collapse of the asset-backed commercial paper markets in August 2007, and the dark grey region correspond with the period following the Lehman Brothers failure in September 2008.