Small Bank Comparative Advantages in Alleviating Financial Constraints and Providing Liquidity Insurance over Time†

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Abstract

Using novel monthly survey data from 1993-2012 on small business managerial perceptions of financial constraints, we address three questions regarding comparative advantages of small banks in alleviating such constraints. 1) Do small banks (still) have these comparative advantages? YES. 2) Do these advantages change over time? YES. They become greater during adverse economic conditions. 3) Do small banks have comparative advantages in providing liquidity insurance to the customers of large banks experiencing liquidity shocks during financial crises? YES. Our findings suggest significant social costs from bank consolidation over time to be weighed against the social benefits.

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1. Introduction

One of the most important issues in finance is the extent to which financial markets and institutions are able to relieve financial constraints – provide firms with the funds to undertake positive net present value projects (e.g., Fazzari, Hubbard, and Petersen, 1988). Small businesses, which represent a significant fraction of employment and economic growth in the United States,[1] are generally considered more financially constrained than large businesses. This is due to a lack of hard, quantitative information, such as verifiable numbers on which to base credit decisions, since small businesses often do not have audited financial statements or publicly-traded securities (e.g., Petersen and Rajan, 1994; Hubbard, 1998; Carpenter and Petersen, 2002). Banks can alleviate small business financial constraints via relationship lending based on soft, qualitative information, such as knowledge of the character of the small business owner, gathered over the course of a relationship in place of hard, quantitative information (e.g., Boot and Thakor, 2000).[2] Small banks are typically viewed as being better at using soft information because such information is easier to communicate within a small organization with fewer layers of management (e.g., Berger and Udell, 2002; Stein, 2002; Berger, Miller, Petersen, Rajan, and Stein, 2005; Liberti and Mian, 2009; Canales and Nanda, 2012; Kysucky and Norden, 2015).[3]

Given the benefits associated with small bank relationship lending, it is potentially concerning that small banks have dropped in number over time. Over 1984 – 2014, the number of small banks in the U.S., measured by those with assets under $1 billion, declined by more than 50%

[1] Small businesses are responsible for 63% of net new jobs created between 1993 and 2013 (Headd, 2014) and account for 46% of private, non-farm gross domestic product in the United States as of 2008 (Kobe, 2012).
[2] The empirical literature confirms the existence of relationship lending benefits (e.g., Petersen and Rajan, 1994; Berger and Udell, 1995; Elsas and Krahnen, 1998; Berlin and Mester, 1999). For reviews of the relationship lending literature, see Boot (2000) and Degryse, Kim, and Ongena (2009).
[3] For example, in a small bank, the loan officer might also be the bank's president and owner, whereas in a large bank, the loan officer may have to justify decisions to senior managers and a credit committee.

from 11,497 to 4,864 (Berger and Bouwman, 2016, Table 8.1). It is possible that something important is being lost – some of the ability to alleviate financial constraints of small businesses.

To address this concern, the paper revisits a classic issue – the role of small banks – but with an empirical approach that has two important advantages over existing studies. First, we use survey responses from randomly sampled small business borrowers that directly capture managerial perceptions of their financial constraints and demand for credit. Second, we have data spanning a 20-year period, allowing us to assess the effects of small bank accessibility over time, across business cycles, and over normal times and financial crises. Specifically, we investigate three questions about the importance of small banks.

Question (1) is: Do small banks (still) have comparative advantages in alleviating financial constraints of small businesses? This question is examined elsewhere in the literature, but our dataset allows us to use a superior measure of small business financial constraints that covers a much longer sweep of time. Additionally, we are better able to address potential endogeneity concerns highlighted below by employing strong controls for confounding factors.

Question (2) is: Do these comparative advantages change over time? Several time-varying factors may affect large and small banks differently, and hence might affect small bank comparative advantages over time. First, comparative advantages of small banks may be higher during adverse economic conditions. Relationship lenders may be able to provide liquidity and interest rate insurance to their borrowers, lending short-term at a loss during such conditions and recouping these losses in later periods (e.g., Sharpe, 1990; Rajan, 1992; Berlin and Mester, 1999; Boot and Thakor, 2000). More recently, it is argued that this may be especially beneficial when economic conditions are adverse (Bolton, Freixas, Gambacorta, and Mistrulli, 2016).[4,5] Small bank comparative advantages may also be greater when financial market conditions are adverse. Small banks tend to finance their relationship loans with relatively stable core deposits (Song and Thakor, 2007). This is particularly beneficial when financial market conditions are adverse and volatile wholesale funding generally used by large banks may dry up rapidly. Finally, there may be a secular decline or increase in small bank comparative advantages. There may be a decline due to improvements in transactional lending technologies or to banking deregulation, both of which favor large banks (e.g., Berger and Udell, 2006).[6] Alternatively, there may be an increase because the small banks that survived consolidation of the industry may be more efficient than those that did not survive.[7]

Question (3) is: Do small banks have comparative advantages in providing liquidity insurance to displaced customers of large banks experiencing liquidity shocks during financial crises? This is a novel but important question, particularly in light of experiences during the recent financial crisis.[8] Ivashina and Scharfstein (2010) document that some large banks rationed credit during the crisis when the relatively volatile, short-term purchased funds market they relied on dried

[4] One reason for this not highlighted by existing theories is that soft information gathered through relationship lending may be more reliable than hard information when times are adverse. For example, a small business owner's character may not lose its effectiveness as much as a credit score during a downturn or during adverse financial market conditions.

[5] Using European data, Beck, Degryse, de Haas, and van Horen (2015) and Bolton, Freixas, Gambacorta, and Mistrulli (2016) provide some evidence suggesting that relationship lending benefits were enhanced during the adverse economic conditions associated with the recent financial crisis. However, they do not focus on small bank comparative advantages.

[6] One example of a transactional lending technology is small business credit scoring, first adopted around the beginning of our sample period. Fair Isaac Corporation introduced the first commercially available model in 1995.

[7] This would be consistent with the efficient structure hypothesis of Demsetz (1973) and Peltzman (1977), under which firms that survive consolidation are generally more efficient than those that do not. There is evidence supporting this hypothesis in banking (e.g., Berger, 1995; Stiroh and Strahan, 2003).

[8] Two recent studies examine related but distinct issues. Beck, Degryse, de Haas, and van Horen (2015) provide evidence that access to relationship lenders reduces the propensity of small and large European firms to become discouraged from seeking bank finance during the recent financial crisis, but not before the crisis. Berger, Cerquiero, and Penas (2015) show that lending to U.S. startup firms is higher in regions with greater shares of small banks just before the crisis, but not during the crisis.

up. It is useful to know whether small banks, which tend to rely on steady, core deposits, provided liquidity insurance to small businesses that were credit rationed by these large banks.[9]

We address these questions using novel monthly survey data on a representative sample of U.S. small businesses from the Small Business Economic Trends (SBET) survey from 1993 – 2012. The survey is conducted by the National Federation of Independent Businesses (NFIB), the largest U.S. small business organization with over 350,000 small business members.[10] The NFIB asks a random sample of its members a set of questions each month. These data allow us to overcome data limitations typically faced in the small business finance literature. In particular, we are able to directly observe managerial assessments of financial constraints. The survey asks borrowing firms whether their borrowing needs are satisfied, capturing the extent to which firms are able to obtain credit when they really want it, as opposed to using indirect constraint measures, such as loan spreads, loan balances, or the use of trade credit, as in the existing literature. The data also provides managerial assessments of firm investment opportunities, which may correspond with credit demand. This is critical since accurately measuring financial constraints and controlling properly for credit demand are major empirical challenges in this literature.

To address Question (1), whether small banks (still) have comparative advantages in alleviating financial constraints of small businesses, we regress a dummy that equals one if a firm perceives its borrowing needs as not satisfied (i.e., it is financially constrained) on the local market share of small banks, defined as the proportion of local branches (i.e., branches within a 50-kilometer radius of the firm) belonging to small banks. The coefficient on small bank share, our key exogenous variable, (inversely) captures the comparative advantages of small banks relative to large

[9] DeYoung, Gron, Torna, and Winton (forthcoming) find evidence that some small banks that focused on small business lending exhibited relatively greater lending during the recent financial crisis, consistent with liquidity insurance, but do not link this lending to liquidity shocks experienced by large banks.
[10] Members include independent businesses and exclude franchises.

banks in alleviating small business financial constraints, the credit supply effect we intend to estimate. It is important to address potential endogeneity concerns, in particular omitted variables related to credit demand as well as indicators of credit supply (other than those we intend to capture) that may be correlated with small bank share. We address this concern by including numerous controls for credit demand (in particular managerial perceptions of firm investment opportunities, local economic conditions, industry × time fixed effects, and location fixed effects) and other measures of credit supply (in particular other local bank characteristics). We find a strong negative association between small bank share and financial constraints, suggesting that firms with better access to small banks are better able to satisfy their financing needs, providing evidence of small bank comparative advantages. While this analysis does not directly facilitate causal inference, we also present numerous robustness checks suggesting that the results are not spuriously driven by potentially omitted factors. The evidence suggests an answer to Question (1) of YES.

To address Question (2), whether these advantages change over time, we first use a simple approach that directly measures small bank comparative advantages as monthly differences in the financial constraints of small businesses with better and worse access to small banks. We regress this measure on a number of aggregate factors, and find that national economic conditions are more important in explaining small bank comparative advantages than financial market conditions and the secular factors mentioned above. We also employ more a rigorous approach that adapts the model used to address Question (1). This approach allows us to test whether small bank comparative advantages vary with economic and financial market conditions and a linear trend, while explicitly controlling for credit demand and other factors. We find that small bank comparative advantages are stronger when economic conditions at both the national and local level are adverse. Thus, both approaches suggest an answer to Question (2) of YES – small bank comparative advantages change over time, increasing when economic conditions are adverse.

Finally, we focus on the recent financial crisis to address Question (3), whether small banks are better at providing liquidity insurance to displaced customers of large banks experiencing liquidity shocks during financial crises. Small businesses in the U.S. experienced more credit rationing than larger firms during the financial crisis (e.g., Montorial-Garriga and Wang, 2012), and similar findings are documented in other nations.[11] No research to our knowledge examines whether banks subject to asset-backed commercial paper (ABCP) market shocks reduced small business lending or whether small banks help mitigate these effects on small businesses.[12] We use an exogenous shock to credit availability for small businesses by identifying small businesses that were more likely to be credit rationed by large banks experiencing liquidity shocks. We do so based on the local presence of large banks with significant pre-crisis exposure to the ABCP market, which was disrupted during the crisis. We find that small businesses located in areas with greater local presence of ABCP banks were more likely to experience financial constraints following these shocks. More important for our question, greater access to small banks significantly mitigated these effects, providing evidence that small banks provided liquidity insurance to the displaced customers of these banks. Thus, the results suggest an answer to Question (3) of YES.

The remainder of this paper is organized as follows. Section 2 describes the data sources. Sections 3 – 5 explain the methodologies and results for Questions (1) – (3), respectively. Section 6

[11] These studies include Cotugno, Monferra and Sampagnaro (2013), Jimenez, Ongena, Peydro, and Saurina (2012), Popov and Udell (2012), and Iyer, Peydro, da-Rocha-Lopes, and Schoar (2013).

[12] Several papers study related topics. Chodorow-Reich (2014) and Karolyi (2015) document that banks with weaker financial health reduced their lending more sharply during the subprime lending crisis, with the effect being more pronounced for lending to smaller firms, and that stronger banking relationships helped mitigate effects from credit supply shocks during this period. Cotugno, Monferra, and Sampagnaro (2013) find similar evidence for small business lending in Italy.

draws conclusions and policy implications. The Appendix provides a geographical description of our sample firms and of our key exogenous variable.

2. Data Sources

We use monthly small business data from June 1993 to December 2012 collected by the National Federation of Independent Businesses (NFIB) in its Small Business Economic Trends (SBET) survey.[13] The NFIB is the largest small business association in the U.S. As of 2015, it has approximately 325,000 member firms of the around 5 million firms of comparable size in the U.S.[14] Around 90% of NFIB firms have under 20 employees, suggesting that the members conform more closely to common definitions of small firms as opposed to medium-sized enterprises. Dunkelberg (1998) provides evidence that NFIB firms provide a reasonable representation of the population of small businesses. The NFIB randomly selects survey participants from its members each month. The number of respondents is approximately 865 per month over the sample period and the key dependent variable, *NotSatisfied* (defined in Section 3.1), is available for firms that classify themselves as borrowers, about 350 respondents per month.[15] The identities of the firms are confidential, but we have access to the 3-digit ZIP code location of the firm.

The SBET survey has key advantages over the more commonly used Survey of Small Business Finance (SSBF), which surveys firms up to 500 full-time equivalent employees every five years from 1988 – 2003, and the Kauffman Firm Survey (KFS), which follows firms that started up

[13] Data are available for a longer time period: on a quarterly basis from 1973:Q1 until 1985:Q4 and on a monthly basis from January 1986 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.
[14] The Small Business Association reports 5.1 million firms with less than 20 employees as of March 2012, the most recent data available.
[15] 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.

in 2004 annually from 2004 – 2011. First, SBET allows us to study firms' survey responses over a much broader sweep of history using a long, continuous monthly time series from June 1993 to December 2012 instead of using data collected every 5 years (SSBF) or only annually from 2004 to 2011 (KFS). Second, it contains firms that are more representative of small businesses as a whole than the KFS, which contains only firms started in 2004. Most important, unlike the SSBF and the KFS, the SBET survey includes the firm manager's perceived financial constraints, as well as perceptions on different aspects of the firm's operations, including economic outlooks, and general business conditions. This allows us to directly measure financial constraints and other firm conditions from the perspective of the small business, rather than resorting to indirect measures, as discussed below.

For each firm, we identify nearby bank branches using the FDIC's annual Summary of Deposits (SoD) dataset from June 1993 to June 2012. Additionally, we obtain quarterly bank Call Report information from 1993:Q1 to 2012:Q3. If the bank belongs to a bank holding company (BHC), we collect Y-9C BHC data over the same time period. County and national population, unemployment rates, and wages are obtained from the Bureau of Labor Statistics.

Our sample includes firms from each of the 48 contiguous states and the District of Columbia. The firms are geographically dispersed, as evidenced in Appendix Figure A.1 Panel A, which presents the geographical density of the firms by county (darker shades indicate greater density). The geographical distribution is quite stable over our 20-year sample period, as evidenced by Appendix Figure A.1 Panels B and C, which present similar information for the first and second halves of the sample period, 1993 – 2002 and 2003 – 2012, respectively. Appendix Figure A.1 Panel D displays population density by county and suggests that the geographical distribution of our sample firms is broadly similar to that of the universe of small businesses.

3. Methodology and Results for Question (1)

This section first discusses the empirical design used to address Question (1) – do small banks (still) have comparative advantages in alleviating small business financial constraints? It then explains the regression variables and provides variable descriptions, sources, and summary statistics in Table 1. Our results suggest that the answer to Question (1) is YES. We find a strong negative association between the local share of small banks and firm financial constraints. The results remain stable in robustness checks, and suggest that small banks (still) possess comparative advantages relative to large banks over the sample period.

3.1 Empirical Design for Question (1)

Our main specification to address Question (1) is an OLS regression model, described below. While the dependent variable used in this model (and in subsequent models) is available at a monthly frequency, the explanatory variables are available at different frequencies: monthly, quarterly, or annually. In every regression equation, the explanatory variables use the most recent information available as of date *t*, indicated for simplicity with subscript *t* throughout the paper.

$$\begin{aligned} NotSatisfied_{i,t} = \; & \alpha_0 + \alpha_1 \, SmallBankShare_{i,t} \\ & + A_2 \, Local\ Market\ Characteristics_{i,t} \\ & + A_3 \, Other\ Local\ Bank\ Characteristics_{i,t} \\ & + A_4 \, Firm\ Characteristics_{i,t} \\ & + Industry \times Time\ FE_{i,t} + State\ FE_i + \varepsilon_{1,i,t} \end{aligned} \qquad (1)$$

The key dependent variable is $NotSatisfied_{i,t}$, our main proxy of financial constraints perceived by management of small business *i* in month *t*. It is a dummy that equals one for each firm 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." Only firms that borrowed or tried to borrow over the last three months answer this question. ~~In the rest of the paper, w~~We refer to these firms collectively as "borrowers" for ease of exposition. Firms that did not try to borrow do not answer this question and are thus excluded from the analyses. This facilitates interpretation because it is ambiguous whether these other firms are discouraged from borrowing or alternatively do not need bank financing. An important advantage of *NotSatisfied* is that it directly corresponds with managerial assessments of financial constraints, which should be more accurate than indirect constraint measures used in the literature, such as loan rates (e.g., Petersen and Rajan, 1994), loan balances (e.g., Berger, Cerquiero, and Penas, 2015), or use of trade credit (e.g., Berger, Miller, Petersen, Rajan, and Stein, 2005).

The key explanatory variable of interest is $SmallBankShare_{i,t}$, the proportion of bank branches belonging to small banks within a 50 kilometer radius of firm *i* in the most recently available June SoD report. This captures the firm's access to small banks, as opposed to its actual banking relationships, which are likely to be endogenous. Using bank location in the absence of observing the actual borrower-bank relationship information is in line with some recent literature (e.g., Beck, Degryse, de Haas, and Van Horen, 2015; Berger, Cerquiero and Penas, 2015). Banks with gross total assets (GTA) up to $1 billion in 2005 real dollars are coded as small banks, consistent with the common research definition of community banks, while others are coded as large banks.[16,17] To calculate the distance between the firm and a bank branch, we use the centroid of the firm's 3-digit ZIP code (the only firm location data available in the survey) and the centroid of the bank branch's 5-digit ZIP code in the most recent SoD data as inputs in the haversine formula.[18]

[16] 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.

[17] The results are similar when using the community bank designations from the FDIC Community Banking Study (2012) available at https://www.fdic.gov/regulations/resources/cbi/data.html or using a $10 billion threshold that is sometimes employed in the literature.

[18] The haversine formula estimates the kilometer distance between locations A and B as:

$d_{A,B} = 2\ R\ \arcsin([\sin^2 (0.5(Y_A\text{-}Y_B)) + \cos(Y_A) \cos (Y_B)\sin^2(0.5*(X_A\text{-}X_B))]^{1/2})$,

where (X_A,Y_A) and (X_B,Y_B) are the coordinates for locations A and B, respectively, and R is the Earth's radius at the poles, or 6,356.752 kilometers.

The coefficient on *SmallBankShare*, α_1, measures the marginal impact of access to small banks relative to large banks in the area on firms' financial constraints, and inversely captures small bank comparative advantages. A negative value for α_1 would imply small bank comparative advantages in relieving financial constraints for small businesses in their markets.

3.2. Control Variables

The control variables in equation (1) include: *Local Market Characteristics*$_{i,t}$ and *Firm Characteristics*$_{i,t}$ to control for credit demand factors, and *Other Local Bank Characteristics*$_{i,t}$ to control for credit supply factors other than that captured by our key exogenous variable, *SmallBankShare*. The baseline model regressions include industry × time (year-month) fixed effects to purge potential heterogeneity in credit demand related to time-varying industry factors.[19] We include state fixed effects to control for unobservable, time-invariant differences across states.[20] Given that the residuals (ε) are unlikely to be independent across the observations, we double cluster standard errors by location and time (year-month).[21]

Other Local Bank Characteristics include bank capitalization, *EqRat*, the average capital ratio of all local banks (i.e., banks with branches within a 50 kilometer radius of the firm). It is calculated as the sum of ((each local bank's equity / GTA) multiplied by the bank's proportion of

[19] The survey classifies firms into ten industry categories. The classifications are self-reported, and include agriculture, retail, wholesale, transportation, manufacturing, construction, professional, services, financial, and other.
[20] It is not possible to include more granular location fixed effects because there are not enough firms in the same smaller geographic unit, such as the 3-digit ZIP code or county.
[21] To be conservative, we use the largest standard errors obtained when double clustering by different geographical dimensions and time. Specifically, we calculate standard errors for each specification three ways based on alternative geographic definitions (the 3-digit ZIP code, the county, and the larger of the two in terms of square kilometers) and time, and use the largest resulting standard errors. Three-digit ZIP codes on average contain 4,802.7 km^2 (median: 3,057.8 km^2) while state counties on average contain 2,225.7 km^2 (median: 1,518.3 km^2). Around 24% of the sample firms are in 3-digit ZIP codes that are smaller than their counties.

local bank branches).[22] Bank illiquidity, *IlliquidityRat*, is the average ratio of the amount of bank liquidity creation to GTA of all local banks. It uses the preferred liquidity creation measure described in Berger and Bouwman (2009) and is weighted in a similar way as *EqRat*.[23] Bank concentration, *DepositHHI*, is the Herfindahl-Hirschman Index of the deposit share of all local banks, calculated using branch-level deposit data.[24] *Branch/Pop* is the ratio of the number of local branches to county population.[25] *FewBanks* is a dummy that equals one if the number of local banks is below the lowest 10th percentile for a particular year.[26]

Local Market Characteristics include *Metro*, a dummy that equals one if the firm is located in a metropolitan area, and zero if it is in a rural area.[27] *ln(LocalPopulation)*, *LocalUnempl*, and *ln(LocalWage)* are the natural log of population, the unemployment rate, and the natural log of the per-capita wage in the firm's county.

Firm Characteristics include managerial assessments of future performance. *ExpGenCond* is the firm's response to the survey question how general business 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 its 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). We also include *ChSales*, which measures how current sales differ from sales over the past three months

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[22] Bank capital has been shown in the literature to be an important factor in bank lending and liquidity creation (e.g., Peek and Rosengren, 1995; Boot and Thakor, 2000; Berger and Bouwman, 2009).
[23] 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 make themselves less liquid. The liquidity creation data were downloaded from http://people.tamu.edu/~cbouwman.
[24] Similar measures are used in Degryse and Ongena (2005, 2007) and Bircan and de Haas (2015).
[25] Results are similar when the numerator is defined as *Bank*, the number of local banks, instead of *Branch*.
[26] This variable focuses on banks instead of branches because a firm that is denied credit at a particular branch will not be able to get credit at any other branch of that bank. Hence, the number of banks in the area is important.
[27] 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. We classify 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.

on a five-point scale, ranging from “much lower” (-2) to “much higher” (+2); *ln(Sales)*, 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)*, the natural log of the lowest number of employees in the firm’s employee category, ranges from “one” to “40 or more;” *Corporation*, *Partnership*, and *Sole Proprietorship,* dummies that equal one if the firm is a corporation, a partnership, and a sole proprietorship or other, respectively, with *Sole Proprietorship* being the excluded category.

3.3. Summary Statistics

Table 1 Panel B displays summary statistics of all variables used in the main analysis for observations with non-missing values for *NotSatisfied*. The sample mean of *NotSatisfied* indicates that 15.5% of the sample firms feel financially constrained. The average proportion of small bank branches in close proximity to sample firms, or *SmallBankShare*, is 42.5%.

Sample firms are almost evenly split between rural and metropolitan banking markets (53% metropolitan). County population is right-skewed – its sample mean and median are 520 thousand and 164 thousand, respectively. Local unemployment averages 5.87% and average local wages are $26.5 thousand.

The average bank appears to have substantial capital (mean *EqRat* of 9.6%), and is approximately equally illiquid on average as in Berger and Bouwman (2016) for 2014:Q4 (0.42 here versus 0.41 there). Our sample banks 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 about one branch per 1,000 population. The mean of *FewBanks* is essentially forced to be about 10%.

Sample firms are generally very small. Average firm sales are approximately \$329 thousand, while the sample median is \$87.5 thousand. The average number of employees is approximately 11, while the sample median is 6. About 69% of the firms are incorporated, while 6% are partnerships. The remaining 25% are sole proprietorships or are self-classified as "other." *ExpGenCond* and *ExpSales* have means of 0.029 and 0.169, respectively, with corresponding standard deviations of 0.771 and 1.001. This implies that firms on average expect general conditions and sales to improve somewhat, but there is considerable variation in both. *ChSales* has a mean of -0.022 and a standard deviation of 0.909, suggesting that sales on average declined slightly over the past three months, but again, there is considerable variation.

3.4. Regression Results for Question (1)

Table 2 Panel A displays the results from regressing *NotSatisfied*, our main measure of small business financial constraints, on *SmallBankShare*, as well as different sets of controls and fixed effects to ensure that the estimates are not driven by our choices of these variables. These models treat small bank comparative advantages as constant over time, which will be revisited when we address Question (2). When including only *SmallBankShare*, local market characteristics, plus time (year-month) fixed effects in Column (1), the *SmallBankShare* coefficient is negative and statistically significant (estimate = -0.068, t-value = -7.47), suggesting that small banks have comparative advantages in alleviating small business financial constraints. The *SmallBankShare* coefficient remains stable when adding controls for other local bank characteristics, firm characteristics, and industry fixed effects in Column (2) (estimate = -0.070, t-value = -7.46), and when replacing the time and industry fixed effects with industry × time fixed effects in Column (3) (estimate = -0.070, t-value = -7.38). Column (4) is the full specification indicated in Equation (1) with all the control variables plus industry × time and state fixed effects. The *SmallBankShare* coefficient is again negative and highly significant, albeit smaller in magnitude (estimate = -0.038, t-value = -3.32). The smaller coefficient when state fixed effects are added may be due to unobservable credit demand not captured by the other controls. However, it may also be due to the fact that small bank proportions tend to be persistent over time within a state. The state fixed effects may absorb some of the effects of *SmallBankShare* we intend to capture, so that these estimates may be viewed as conservative.

The results are also economically significant. When the proportion of local branches belonging to small banks increases from the 25^{th} to the 75^{th} sample percentile (i.e., *SmallBankShare* moves from 21.9% to 59.1%), the proportion of small businesses that feel constrained decreases by 9.1%.[28] Thus, the data strongly suggest that small banks have comparative advantages in alleviating financial constraints.

The control variable coefficient signs are generally consistent with intuition.

3.5. Robustness Checks for Question (1)

To assess the robustness of the Question (1) results, we perform numerous checks: we use a non-linear model; we run regressions separately for metropolitan and rural areas; we use alternative measures of small bank access; we include additional control variables; and we use alternative measures of financial constraints.[29]

[28] Specifically, the predicted value of *NotSatisfied* based on the full specification in Column (4) decreases by (59.1% - 21.9%) * 0.038 = 1.41 percentage points, which is 9.1% of the sample mean.

[29] A potential sample selection issue arises because not all sample firms seek financing. *NotSatisfied*, is only available for 46.3% of the observations. Firms that do not answer the borrowing questions may not seek financing either because they are discouraged from applying or because they do not need external financing. A raw data comparison suggests it is more likely the former: non-borrowers tend to have fewer employees, lower sales, and weaker sales prospects. While we cannot fully address this sample selection issue, we run a regression in which we add non-borrowers to our sample and assign a value of one for *NotSatisfied*. We obtain a similar *SmallBankShare* coefficient (estimate = -0.04276, t-value = -3.78).

3.5.1. Non-Linear Model

The main results are obtained using OLS rather than the more commonly used logit form that would force the predicted values for *NotSatisfied* inside the 0-1 range. We do so for two reasons. First, it is important to include industry × time and state fixed effects for reasons explained above, and including fixed effects in a logit model yields incidental parameter bias (Wooldridge, 2010). That is, the inclusion of fixed effects in a logit specification would cause the number of parameters to grow with the number of observations, meaning that the parameter estimates cannot converge to their true value as the sample size increases, yielding biased parameter and standard error estimates. Second, the variables of interest in the regressions used to address Questions 2 and 3 are double and triple interaction terms, which create problems in nonlinear models.[30]

Nonetheless, to check the robustness of our Question 1 results, we use a logit specification that includes all the control variables from the baseline OLS regression model (Table 2 Column (4)), but with fixed effects excluded to avoid incidental parameter bias. Table 3 Panel A shows that the marginal effect of *SmallBankShare* is negative, statistically significant, and comparable to the OLS estimate, suggesting robustness.

3.5.2. Metropolitan versus Rural Areas

We also rerun our main regression separately for metropolitan and rural markets to address two potential concerns. The first is that *SmallBankShare* may be different in metropolitan and rural markets and this may be driving our results. An informal way to address this is to compare population density (Appendix Figure A.1. Panel D) with *SmallBankShare*'s geographical distribution (Appendix Figure A.1 Panel E). This comparison shows that *SmallBankShare* takes on

[30] To evaluate interaction effects in a nonlinear model, one cannot look at the signs, magnitudes, or significance of the coefficients on the interaction terms (Norton, Wang, and Ai, 2004; Powers, 2005), but rather one has to calculate marginal effects. While this can be done for double interaction terms, the calculations become much more complicated for triple interaction terms.

higher values in less populated regions (darker shades indicate higher values). This is not surprising, given that large banks are attracted to large business customers that are generally located in more populous markets. A formal way to address this concern is to show that our main results hold in both metropolitan and rural markets and we do this below.

The second potential concern is measurement error. As noted above, we know each firm's 3-digit ZIP code, but not its exact address, so we calculate the firm's access to small banks somewhat imprecisely using a 50-km radius around the centroid of the firm's 3-digit ZIP code. This measurement error is not likely to be substantial in metropolitan areas, where 3-digit ZIP codes tend to be small and the firm's location can thus be measured relatively accurately. In contrast, the error may be substantial in some cases in rural areas, where 3-digit ZIP codes are generally larger, although these cases are rare.[31] Running the regression separately for metropolitan and rural markets affords an opportunity to see if this measurement error may have significant effects on the results.

In Table 3, Panel B Columns (1) and (2), we re-estimate the model separately for metropolitan and rural subsamples, i.e., observations for which *Metro* takes the values 1 and 0, respectively. The *SmallBankShare* coefficient is statistically and economically significant in both subsamples, suggesting that neither of the potential concerns appear to drive our main results.

3.5.3. Alternative Measures of Small Bank Access

As an alternative way to address the imprecise calculation of the local banking markets for the firms noted above, we next use the proportion of small-bank branches located within the firm's 3-digit ZIP code instead of within a 50-kilometer radius of the firm. Using this approach in Table 3 Panel

[31] Three-digit ZIP codes are generally smaller than a circular area with a radius of 50 km: 3-digit ZIP codes on average contain 4,802.7 km^2 (median: 3,057.8 km^2), whereas a circular region with a radius of 50 km contains 7,853.9 km^2. Fewer than 10% of the sample firms are in a 3-digit ZIP code that is larger than a circular area with a 50-km radius.

C Column (1), we obtain similar results. Using alternative cutoffs of 30 and 100 kilometers in Table 3 Panel C Columns (2) and (3) yields comparable results.[32]

The denominator of *SmallBankShare* is the number of local bank branches belonging to small and large banks. It may inadvertently measure the degree of competition from nearby large banks instead of capturing access to small banks. To address this concern, we create an alternative small bank access variable, the natural log of (one plus (the number of small bank branches scaled by local population)), which does not rely on large-bank branches. Table 3 Panel C Column (4) shows that the coefficient on this alternative measure is negative and significant, suggesting that the results capture small bank accessibility rather than competition from large banks.

We also perform a robustness check that replaces our time-varying *SmallBankShare* variable with its values in 1992, right before the start of the sample period. This mitigates endogeneity concerns about *SmallBankShare* inadvertently being caused by the dependent variable or by other factors during the sample period, since it is difficult for the future to cause the past. Table 3 Panel C Column (5) shows that the use of this time-invariant *SmallBankShare* measure yields comparable results to our main findings. This may not be surprising, since the correlation of *SmallBankShare* across different local markets between its values in 1992 and 2012 is 78%. As an alternative, we lag *SmallBankShare* by three years and obtain similar results in Table 3 Panel C Column (6).

3.5.4. Additional Control Variables

Deregulation in the banking sector may have affected not just *SmallBankShare* but also *NotSatisfied* in profound ways.[33] For example, better-run small banks may be more likely to survive the competitive shakeout that follows deregulation, and these banks may also supply more credit. Our

[32] We obtain similar results when we capture small bank accessibility using an alternative *SmallBankShare* definition based on deposit share instead of branch share. This alternative definition based on the level of deposits is arguably inferior since it may capture bank funding conditions, which are likely endogenous to the amount of credit issued.
[33] Since deregulation likely affects both directly, it cannot be used as an instrument for *SmallBankShare*.

main regressions to some extent control for this via the inclusion of state fixed effects, which account for state deregulation events that occurred prior to our sample period in 1993. However, we go further by including a specification that controls for when the firm's state adopted interstate branching deregulation following the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994.[34] In Table 3 Panel D Column (1), we find that the results are not sensitive to the inclusion of these additional controls.

Our main regressions already control for credit demand by including a number of local market characteristics. To further mitigate concerns that the results are driven by areas with weaker banking conditions or greater credit demand, we consider here two additional factors: local bank failures and local house price indices.[35,36] Table 3 Panel D Columns (2) and (3) show that our main results are robust to including local bank failures or housing market conditions.

3.5.5. Alternative Measures of Financial Constraints

We next consider whether our results also hold when using three alternative financial constraint measures from the survey. First, *ExpectedDifficulty* is a dummy that equals one if the firm expects to experience increased financing difficulty in the next three months.[37] This measure is only available for respondents who borrow at least once every three months. Second, *LoanSpread* is the loan interest rate paid minus the 3-month Treasury bill yield for the month of the survey.[38] This measure is available for most firms that respond to the question used to construct *NotSatisfied*. Third,

---

[34] We cannot directly control for deregulation events that took place prior to Riegle-Neal because our sample period starts in 1993.
[35] We calculate the proportion of local branches belonging to banks that failed in the prior 12 months.
[36] We use quarterly house price indices from the Federal Housing Finance Agency (FHFA): the MSA-level index when the firm is located in an MSA and the state-level index otherwise.
[37] This measure is based on the question: "Do you expect to find it easier or harder to obtain your required financing during the next three months?"
[38] This measure is based on the question: "If you borrowed within the last three months for business purposes, and the loan maturity was 1 year or less, what interest rate did you pay?" The survey does not include information about the loan type (term loan or line of credit) or other loan contract terms, such as collateral and maturity.

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.[39] This measure is only available for respondents who borrow at least once every three months.

In Table 3 Panel E, the *SmallBankShare* coefficient in the *ExpectedDifficulty* regression is negative and significant and economically comparable to the main results using *NotSatisfied*. The coefficients on *SmallBankShare* in the *LoanSpread* and *RateChange* models are also negative and statistically significant, but their economic magnitudes are small. When *SmallBankShare* increases from the 25th to the 75th sample percentile (i.e., from 21.9% to 59.1%), *LoanSpread* decreases by a mere 0.044 percentage points while *RateChange* drops by 0.011, which is also minor since *RateChange* is measured using a 5-point scale. The smaller economic significance for *LoanSpread* and *RateChange* than for *NotSatisfied* and *ExpectedDifficulty* results suggest that credit prices are generally less important than credit availability to small businesses.

4. Methodology and Results for Question (2)

This section discusses the methodology and results for Question (2) – do small bank comparative advantages in alleviating small business financial constraints change over time? Our results suggest that the answer is YES: they are stronger during adverse economic conditions, consistent with small banks providing liquidity insurance to their small business customers.

To address Question (2), we focus on factors identified in the Introduction that may affect large and small banks differently, and hence might influence small bank comparative advantages over time: economic conditions, financial market conditions, and secular factors. Specifically, we

[39] This measure is based on 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?"

examine if small bank comparative advantages are higher when economic and financial market conditions are adverse, and whether they generally decline or increase over time. We use two approaches for this purpose. The first is a simple approach used to alleviate potential data snooping concerns. The second uses more rigorous econometric methods and provides similar intuition.

4.1 Simple Approach to Address Question (2)

The simple approach attempts to directly link economic conditions, financial market conditions, and a linear trend to small bank comparative advantages. To do so, we first construct a time-varying measure of small bank comparative advantages: it captures the differences in financial constraints between small businesses with better and worse access to small banks at each point in time. Specifically, $SmallBankCompAdv_t$ is the difference in the average *NotSatisfied* of firms with *SmallBankShare* values above versus below the sample median at time t. This variable is comparable to the *SmallBankShare* coefficient estimated in Equation (1), but is simpler to construct and yields point-in-time estimates of small bank comparative advantages.

We next regress monthly $SmallBankCompAdv_t$ values on several proxies for economic and financial market conditions and a linear trend:

$$\begin{aligned} SmallBankCompAdv_t \quad &= \gamma_0 + \gamma_1\, Nat'lUnempl_t \\ &+ \gamma_2\, ln(Nat'lWage)_t \\ &+ \gamma_3\, SystemicRisk_t \\ &+ \gamma_4\, FedFunds_t \\ &+ \gamma_5\, LinearTrend_t \\ &+ \varepsilon_{3,t} \end{aligned} \tag{2}$$

where *Nat'lUnempl* is the national unemployment rate, *ln(Nat'lWage)* is the natural log of national wage per capita, *SystemicRisk* is aggregate systemic risk (SRISK) as in Brownlees and Engle (2016), which has been used in other banking research (e.g., Karolyi, Sedunov, and Taboada, 2016),[40] *FedFunds* is the month-end federal funds rate, and *LinearTrend* is the number of months since the start of the sample period. To address potential concerns related to dependence in the residuals, we use heteroskedasticity- and autocorrelation-consistent standard errors to construct the test statistics.

Figure 1 plots the monthly *SmallBankCompAdv* values as gray dots over time, where negative values indicate small bank comparative advantages. To help visualize the pattern, a Loess smoother is applied to the monthly estimates, displayed as the solid black line. The first and last 18 months are excluded, given that kernel regression output is difficult to interpret at the initial and end ranges. The average *SmallBankCompAdv* over the entire sample period is -0.046, implying that the proportion of small businesses experiencing financial constraints is 4.6 percentage points lower when firms have better access to small banks. This is quite large relative to the sample mean for *NotSatisfied* of 0.155. The figure suggests that *SmallBankCompAdv* varies quite a bit over time. It began to strengthen substantially at the start of the recent financial crisis and associated economic problems, and peaked shortly after the end of the crisis.

Table 4 shows the results of Equation (2), in which the monthly *SmallBankCompAdv* values are regressed on the national economic and financial market conditions and a linear trend. Columns (1) – (5) display the results for *Nat'lUnempl*, *ln(Nat'lWage)*, *SystemicRisk*, *FedFunds*, and *LinearTrend*, respectively. Each of the variables is statistically significant with the predicted sign in Columns (1) – (4), suggesting that small bank comparative advantages increase with adverse economic and financial market conditions. *LinearTrend* is statistically insignificant with a negative coefficient. These variables are highly collinear, making it difficult to disentangle the underlying

[40] Details about the calculation of aggregate systemic risk are given in Table 1. The authors thank John Sedunov for providing us with this variable.

causes of why small bank comparative advantages change over time.[41] Column (6) addresses this by including all the variables in the same regression, and shows that only *Nat'lUnempl* remains statistically significant. Its coefficient is comparable to that in Column (1) despite the high degree of collinearity.

The coefficient of -1.865 on *Nat'lUnempl* in Column (6) is also economically significant. It suggests that if the unemployment rate were one percentage point higher, 1.9 percentage points more small businesses would experience financial constraints when they have worse access to small banks compared to those with better access. This effect is sizable when compared to the sample mean of *SmallBankCompAdv*, which is -0.046. While these tests do not control properly for credit demand, they provide the basic intuition for the more rigorous approach we present next.

4.2. Alternative Approach to Address Question (2)

To address whether small bank comparative advantages change over time while accounting for credit demand, we return to the pooled regression model of Equation (1) that includes various controls, including ones for credit demand. We modify it and add *SmallBankShare* interacted with the national economic and financial market conditions as well as the linear trend. The uninteracted values of the aggregate condition variables are subsumed by the industry × time fixed effects. The resulting model is:

$$
\begin{aligned}
NotSatisfied_{i,t} = {} & \theta_0 + \theta_1\, SmallBankShare_{i,t} \\
& + \theta_2\, SmallBankShare_{i,t} \times Nat'lUnempl_t \\
& + \theta_3\, SmallBankShare_{i,t} \times ln(Nat'lWage)_t \\
& + \theta_4\, SmallBankShare_{i,t} \times SystemicRisk_t \\
& + \theta_5\, SmallBankShare_{i,t} \times FedFunds_t \\
& + \theta_6\, SmallBankShare_{i,t} \times LinearTrend_t \\
& + \Theta_7\, Local\ Market\ Characteristics_{i,t} \\
& + \Theta_8\, Other\ Local\ Bank\ Characteristics_{i,t}
\end{aligned}
$$

[41] The absolute value of the correlation coefficients among the five variables ranges from 53.4% to 97.5%.

$$+\ \Theta_9\ Firm\ Characteristics_{i,t}$$
$$+\ \Theta_{10}\ Industry \times Time\ FE_{i,t}$$
$$+\ \Theta_{11}\ State\ FE_i + \varepsilon_{4,i,t} \qquad (3)$$

The interaction terms θ_2 through θ_6 indicate how the effects of *SmallBankShare* vary with economic, financial market, and secular factors over time, and are comparable to those in Equation (2).

Table 5 adds the double interaction terms to the baseline regression model of Equation (1) iteratively to make the presentation comparable to that in Table 4. Columns (1) – (4) reveal that each national economic and financial market condition interaction term is statistically significant when added to the model in isolation, while the interaction term with *LinearTrend* is statistically insignificant. Column (6) shows that only the *SmallBankShare* × *Nat'lUnempl* interaction term remains statistically significant when including all the interaction terms.

The results are comparable to those of Table 4, suggesting that, even after explicitly controlling for credit demand, small bank comparative advantages do change over time, driven by adverse economic conditions. The coefficients on the *Nat'lUnempl* interaction term range from -2.822 to -4.135, comparable to the coefficients on *Nat'lUnempl* in Table 4. In terms of economic significance, if *Nat'lUnempl* were one percentage point higher, the *SmallBankShare* coefficient would be between 0.0282 and 0.0414 lower, approximately doubling the effect of the uninteracted *SmallBankShare* coefficient.

The results provide evidence that small bank comparative advantages are stronger when national economic conditions are adverse. We also check whether these advantages are stronger when local economic conditions are adverse and whether the result at the national level survives. We therefore add interaction terms between *SmallBankShare* and local economic conditions (*LocalUnempl* and *ln(LocalWage)*) to Equation (3). Table 5 Column (7) shows that the coefficients on both of the local interaction terms are statistically significant and signed according to predictions.[42] Even with the inclusion of these additional terms, the interaction term for *Nat'lUnempl* remains statistically significant. Thus, the results suggest that adverse local and national economic conditions both increase small bank comparative advantages.

To address potential concerns that the results may be driven by credit demand effects related to regions that experience persistently adverse economic conditions, we perform an additional robustness check in which we control for the average local economic conditions over the sample period and its interaction with *SmallBankShare*. Table 5 Column (8) shows that the results remain significant, suggesting that they are not driven by persistent differences in economic conditions across local markets.

5. Methodology and Results for Question (3)

This section discusses the methodology and results for Question (3) – do small banks also have comparative advantages in providing liquidity insurance to displaced customers of large banks experiencing liquidity shocks during financial crises? To address this question, we focus on the funding shocks caused by the disruptions in the asset-backed commercial paper (ABCP) market during the recent financial crisis. We show that small businesses with greater exposure to these banks are more likely to experience financial constraints, and the local share of small banks mitigates these effects, suggesting that the answer to Question (3) is YES.

5.1. Initial Check: Are ABCP Market Exposure and Small Business Lending Linked?

[42] While the *ln(Nat'lWage)* interaction term is not significant, the *ln(LocalWage)* interaction term is, possibly because of greater variability.

To establish an initial link between large banks' ABCP market exposure and small business lending, we examine annual growth rates of small business loan originations for large banks in holding companies that do and do not have ABCP market exposure in the prior year. Holding company level ABCP exposures are used since bank level exposures are generally not available. We use Community Reinvestment Act (CRA) data, in which large banking institutions report their small business loan originations as of December of each year.[43] We view loans up to $1 million to businesses with annual revenues under $1 million as small business loans.

We find that large banks with and without ABCP market exposure reduced small business loan originations by 36.5% and 20.1%, respectively, during 2008 – 2009 (not tabulated for brevity). The more pronounced decline at large banks with ABCP exposure suggests that the liquidity shock to these banks indeed increased credit rationing of small business borrowers. These results are consistent with Ivashina and Scharfstein (2010) who find a reduction in overall lending by large banks whose holding companies had large exposure to the ABCP market during the crisis.

5.2. Methodology Used to Address Question (3)

To address Question (3), we focus on the change in small bank comparative advantages from before to during disruptions in the ABCP market across local areas with high versus low ABCP exposure (i.e., triple differencing). If better access to small banks mitigates the effects of credit rationing due to shocks in the ABCP market, then small bank comparative advantages would increase more for small businesses in markets with higher ABCP exposure during the shock period.

We split the financial crisis into two parts to distinguish between distinct ABCP market disruption periods. $CRISIS_t^{ABCPMktShock}$ is a dummy that equals 1 from August 2007, when disruptions

[43] We are able to match approximately 90% of large banks in the Call Report dataset to the CRA dataset.

in the ABCP markets first occurred, through September 2008, the month when the Federal Reserve initiated its ABCP Money Market Mutual Fund Liquidity Facility (AMLF) and the Lehman Brothers' bankruptcy occurred.[44] $CRISIS_t^{GeneralMktShock}$ is a dummy that equals 1 from October 2008, the month after the initiation of the AMLF and Lehman Brothers' bankruptcy, through February 2010, the end of the AMLF program. We expect stronger effects for small businesses in markets with higher ABCP exposure during the first period ($CRISIS_t^{ABCPMktShock}$) than the second period ($CRISIS_t^{GeneralMktShock}$) because the latter includes the aftermath of Lehman Brothers' collapse and the resulting disruptions in other short-term debt markets that likely affected markets more broadly.

We examine how the effects of *SmallBankShare* on *NotSatisfied* differ for small businesses in markets with high ABCP exposure ($HighABCPExposure_i$ discussed below) during the shock periods using triple-differencing in the following regression model:

$$
\begin{aligned}
NotSatisfied_{i,t} \quad & = \rho_0 + \rho_1\, SmallBankShare_{i,t} \\
& + \rho_2\, HighABCPExposure_i \\
& + \rho_3\, SmallBankShare_{i,t} \times HighABCPExposure_i \\
& + \rho_4\, SmallBankShare_{i,t} \times CRISIS_t^{ABCPMktShock} \\
& + \rho_5\, HighABCPExposure_i \times CRISIS_t^{ABCPMktShock} \\
& + \rho_6\, SmallBankShare_{i,t} \times HighABCPExposure_i \times CRISIS_t^{ABCPMktShock} \\
& + \rho_7\, SmallBankShare_{i,t} \times CRISIS_t^{GeneralMktShock} \\
& + \rho_8\, HighABCPExposure_i \times CRISIS_t^{GeneralMktShock} \\
& + \rho_9\, SmallBankShare_{i,t} \times HighABCPExposure_i \times CRISIS_t^{GeneralMktShock} \\
& + P_{10}\, Other\ Local\ Bank\ Characteristics_{i,t} \\
& + P_{11}\, Local\ Market\ Characteristics_{i,t} \\
& + P_{12}\, Firm\ Characteristics_{i,t} \\
& + Industry \times Time\ FE_{i,t} + State\ FE_i + \varepsilon_{5,i,t} \qquad (4)
\end{aligned}
$$

The parameters of interest are the coefficients on the triple interaction terms, $SmallBankShare_{i,t} \times HighABCPExposure_i \times CRISIS_t^{ABCPMktShock}$ and $SmallBankShare_{i,t} \times HighABCPExposure_i \times$

[44] Kacperczyk and Schnabl (2010) show that trouble in the ABCP market started in August 2007 (i.e., ABCP outstandings decreased and spreads over the federal funds rate increased sharply), following the collapse of several hedge fund subsidiaries of Bear Stearns. The ABCP markets became further stressed following the collapse of Lehman Brothers in September 2008, after which point the Asset-backed Commercial Paper Money Market Mutual Fund Liquidity Facility (AMLF) program was initiated by the Federal Reserve to alleviate some of these resulting effects. After these markets were stabilized, the AMLF was closed in February 2010.

$CRISIS_t^{GeneralMktShock}$. Recalling that a negative coefficient on *SmallBankShare* implies greater small bank comparative advantages, negative signs on the triple interaction terms would suggest that such comparative advantages increased more in areas where large banks were more exposed to ABCP, consistent with small bank provision of liquidity insurance to displaced customers of large banks experiencing liquidity shocks during financial crises.

$HighABCPExposure_i$ measures the extent to which the banking market in which small business *i* is located has high large-bank exposure to the ABCP market before the crisis. We follow a two-step process to construct it. In Step 1, we identify banks heavily dependent on ABCP as of 2006:Q2 (well before the start of the crisis to avoid potential bias from the effects of ABCP market disruptions on a bank's ABCP exposure during the crisis).[45] Specifically, we define an individual bank to be a high ABCP bank if its BHC's ABCP exposure relative to BHC-level equity capital > 40%, the median value for all BHCs with positive exposure as of 2006:Q2. That is, $HighABCPBank_i^{06:Q2} = 1$ if $\left(\frac{BHC\ ABCP\ Exposure_i^{06:Q2}}{BHC\ Equity_i^{06:Q2}}\right) > 40\%$. We normalize ABCP exposure by equity capital because the shock is expected to have a strong effect on lending only when the BHC does not have sufficient capital to absorb the shock.

In Step 2, we construct two alternative measures of *HighABCPExposure* for firm *i* based upon the local market share (i.e., within a 50-kilometer radius) of the high ABCP banks before the crisis. Our first measure is continuous, the proportion of local branches belonging to high ABCP banks for each branch *j* located in the local market:

[45] As in Boyson, Fahlenbrach, and Stulz (2014), we measure the total dollar ABCP exposure of a BHC using FR Y-9C data on credit (BHCKB806 and BHCKB807) and liquidity (BHCKB808 and BHCKB809) exposures for conduits sponsored by the bank, bank affiliates, and other institutions. Acharya, Schnabl, and Suarez (2013) use a similar measure. The measure reflects disruptions in the ABCP market, which created severe liquidity issues for large banks that heavily used ABCP funding either because they had trouble rolling over these short-term funds or because they sponsored conduits which suffered from extensive borrower drawdowns.

$$HighABCPExposure_i^{Continuous} = \frac{\sum_{dist(i,j)<50km}\left(\#Branches_j^{06:Q2} \times HighABCPBank_j^{06:Q2}\right)}{\sum_{dist(i,j)<50km}\left(\#Branches_j^{06:Q2}\right)} \quad (5)$$

Our second measure is a dummy that identifies areas with a very high presence of branches of high ABCP banks, areas above the 80th percentile[46] based on $HighABCPExposure_i^{Continuous}$:

$$HighABCPExposure_i^{Dummy} = 1 \; if \; rank\left(HighABCPExposure_i^{Continuous}\right) > 80th \; percentile \quad (6)$$

Both measures should capture markets where firms are more likely to be displaced due to liquidity shocks, but the dummy variable results are easier to interpret.

The sample period to address Question (3) starts one year before the initial disruptions in the ABCP markets, or August 2006.[47] The sample period ends in February 2010, the month when the AMLF was closed, given that the ABCP markets had been stabilized by that point.

5.3. Regression Results for Question (3)

Table 6 presents the results. Column (1) uses the continuous measure for *HighABCPExposure*, while Column (2) uses the dummy measure.

The coefficients on the triple interaction term that focuses on the first part of the crisis when disruptions were largely concentrated in the ABCP market, *SmallBankShare* × *HighABCPExposure* × $CRISIS^{ABCPMktShock}$, are large, negative, and highly statistically significant. As expected, the triple interaction term coefficients that focus on the second part of the crisis when more markets were disrupted are smaller and only statistically significant in one model. Overall, these results suggest that small banks have comparative advantages in providing liquidity insurance to displaced small business customers of large banks experiencing liquidity shocks during financial crises.

[46] The results are similar using the 90th percentile.
[47] ABCP exposure is measured as of 2006:Q2 given that we do not have monthly data for this information.

5.4. Robustness Checks for Question (3) Results

We perform several robustness checks for Question (3). First, in Section 3.5.4, we examined whether the results could be explained by local banking and housing market conditions, and found that they could not. During the financial crisis, there was substantial regional variation in both. To address potential concerns that such variation may drive our results, we rerun the regressions while controlling for local bank failures and the local house price index. Columns (1) and (2) of Table 7 show that the coefficients on the triple interaction terms remain stable, suggesting that these concerns are not warranted.

Second, the tests above view every bank in the local market as a possible provider of liquidity insurance to the displaced borrowers, including banks with high ABCP market exposure. However, such banks are unlikely to provide liquidity insurance since they themselves are affected by disruptions in the ABCP market. We therefore construct an alternative *SmallBankShare* measure that excludes ABCP bank branches and rerun our regressions. Columns (3) and (4) of Table 7 show that we obtain similar results using this alternative measure.

6. Conclusions and Policy Implications

We address questions related to small bank comparative advantages in alleviating small business financial constraints using a superior dataset, the Small Business Economic Trends (SBET) survey, which allows us to measure financial constraints from the perspective of the small businesses. We find that: (1) small banks (still) have comparative advantages; (2) such advantages are greater when economic conditions are adverse, consistent with the provision of liquidity insurance to their small business customers; and (3) the advantages extend to the provision of liquidity insurance to displaced customers of large banks experiencing liquidity shocks during financial crises.

Our findings have policy implications. There has been a dramatic decline in the number of small banks over the past few decades, and we document that the local market share of small banks (*SmallBankShare*) has dropped by 23 percentage points from 59% in 1993 to 36% in 2012. Our results suggest that, if *SmallBankShare* had been at its 1993 level in 2012, the proportion of small businesses experiencing financial constraints would have been 11 percentage points lower, which is very large compared to the sample mean of 15.5%. Our results suggest that consolidation in the banking sector may be associated with significant social costs given the critical role of small businesses in the economy and given the comparative advantages of small banks in dealing with such businesses. Specifically, the reduction in small bank market shares may result in reduced economic growth and employment, and may leave the economy more prone to the vagaries of the business cycle and financial crises.[48] These costs should be added to other social costs of consolidation and must be weighed against the benefits of bank consolidation, such as scale efficiencies enjoyed by large banks (e.g., Berger and Mester, 1997; Wheelock and Wilson, 2012; Hughes and Mester, 2013)).[49]

In closing, we bring up the possibility that alleviating financial constraints at small businesses may not always be socially beneficial. It has been argued that entrenched, inefficient managers of some small banks may routinely fund negative net present value investments at small businesses (e.g., Berger, Kashyap, and Scalise, 1995). We cannot directly assess this, as investment outcomes are unobservable in the survey data. However, in untabulated results, we find that higher

[48] Consistent with this conclusion, Nguyen (2014) finds that branch closings following bank mergers lead to prolonged reductions in small business lending. Several studies also provide evidence that reductions in credit availability to small firms affect employment (e.g., Fort, Haltiwanger, Jarmin, and Miranda, 2013; Chodorow-Reich, 2014; Greenstone, Mas and Nguyen, 2015), although these studies do not focus on small bank lending.

[49] Such policies include: competition-related antitrust enforcement; legislation such as the Riegle-Neal Act of 1994 that allows interstate bank mergers, but limits the deposits of individual banks through these mergers to 10% of the U.S. total; prudential supervision, such as stress tests required by the Dodd-Frank Act that are applied differently by bank size class; and relatively fixed regulatory compliance costs that may encourage consolidation to economize on these costs.

SmallBankShare reduces one-year ahead county unemployment rates, while it has no effect on future county wages. While admittedly rudimentary, these results may help allay concerns that additional small business lending by small banks is used to fund negative NPV investments. More research in this area may be helpful.

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Figure 1: Small Bank Comparative Advantages over Time

This figure shows monthly values of *SmallBankCompAdv*, the difference in the average *NotSatisfied* of firms with *SmallBankShare* values below versus above the sample median at time *t*, as gray dots. The fitted curve (solid black line) is constructed using a Loess smoother with a bandwidth parameter of 0.1 and is shown for the period January 1995 – June 2011. The first and last 18 months of the sample period are excluded, given that kernel regression output is difficult to interpret at the initial and end ranges.

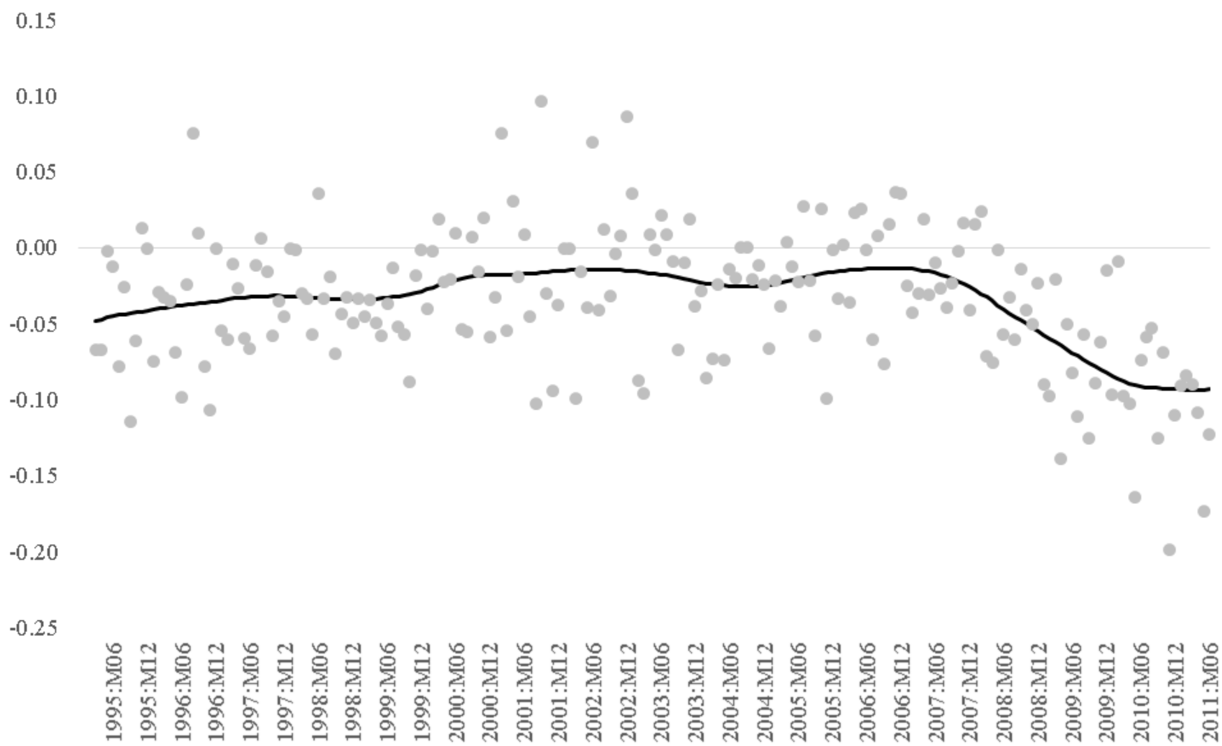

Table 1: Variable Descriptions, Sources, and Summary Statistics

The analyses use data from several sources: firm-level data from the Small Business Economic Trends (SBET) survey, available on a monthly basis from June 1993 – December 2012; Summary of Deposits (SoD) data available annually in June; annual Census Bureau (Census) data; quarterly bank Call Report data; 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 available values. Panel A briefly describes the regression variables and gives the data sources. Panel B displays summary statistics based upon the sample for which *NotSatisfied* is available. Sample percentiles and standard deviations are not displayed for dummies because they follow trivially from the means.

Panel A: Variable Descriptions

Variable	Description	Source
Key Dependent Variable:		
NotSatisfied	Dummy that equals one if the firm did not satisfy its borrowing needs in the past 3 months for all firms that sought financing within the previous three months	SBET
Alternative Dependent Variables:		
ExpectedDifficulty	Dummy that equals one if it will be harder for the firm to get financing in the next 3 months	
LoanSpread	Interest rate (in percentage points) paid by the firm on loans with maturities less than or equal to one year originated within the past three months minus the 3-month Treasury Bill yield	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)	SBET
Key Explanatory Variable:		
SmallBankShare	Proportion of bank branches within a 50-km radius of the firm that belong to small banks. Small banks have gross total assets (GTA) up to $1 billion in 2005 real dollars. GTA equals total assets plus allowances for loan and lease losses and the allocated risk transfer.	Call Reports, SoD
Control Variables:		
<u>Local Market Characteristics:</u>		
Metro	Dummy that equals one if the firm is located in a metropolitan statistical area (MSA) or New England county metropolitan area (NECMA), and zero otherwise.	
LocalPopulation	Population size in the county in which the firm is located	Census
LocalUnempl	Unemployment rate in the county in which the firm is located	BLS
ln(LocalWage)	Natural log of per-capita wages in the county in which the firm is located	BLS
<u>Other Local Bank 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 (Cat Fat to GTA) for banks 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
FewBanks	Dummy that equals 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
<u>Firm Characteristics:</u>		
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
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	Dummy that equals one if the firm is incorporated as a corporation, and zero otherwise	SBET
Partnership	Dummy that equals one if the firm is incorporated as a partnership, and zero otherwise	SBET
Proprietorship	Dummy that equals one if the firm is a proprietorship or other, and zero otherwise (Omitted from the regressions to avoid perfect collinearity)	SBET

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Other Factors:		
Nat'Unempl	Unemployment rate at the national level	BLS
ln(Nat'lWage)	Natural log of per-capita wages at the national level	BLS
SystemicRisk	Aggregate systemic risk (SRISK) as in Brownlees and Engle (2016). SRISK captures a financial institution's capital shortfall conditional on a severe market decline. Daily values are constructed as the sum of the dollar shortfalls across large U.S. financial institutions. The analysis uses the natural log of monthly values (average of daily values) as it is highly right skewed.	CRSP / Compustat
FedFunds	The Federal Funds rate at the end of each month	FRED
LinearTrend	The number of months since the start of the sample period	

Panel B: Summary Statistics

	N	Mean	StDev	25th Pct.	Median	75th Pct.
Dependent Variables:						
NotSatisfied	76973	0.155				
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	76973	0.425	0.248	0.219	0.383	0.591
Control Variables:						
Local Market Characteristics:						
Metro	76973	0.532				
LocalPopulation (thou) (regressions use the natural log)	76973	520.648	1154.006	48.662	164.581	500.926
LocalUnempl	76973	5.870%	2.707%	3.900%	5.300%	7.200%
LocalWage ($thou) (regressions use the natural log)	76973	26.481	16.617	14.627	22.834	34.535
Other Local Bank Characteristics:						
EqRat	76973	0.096	0.012	0.088	0.095	0.103
IlliquidityRat	76973	0.423	0.413	0.322	0.384	0.440
DepositHHI	76973	0.147	0.091	0.089	0.129	0.178
Branch/Pop	76973	0.001	0.002	0.000	0.001	0.002
FewBanks	76973	0.104				
Firm Characteristics:						
ExpGenCond	76973	0.029	0.771	0.000	0.000	0.000
ExpSales	76973	0.169	1.001	-1.000	0.000	1.000
ChSales	76973	-0.022	0.909	-1.000	0.000	1.000
Sales ($thou) (regressions use the natural log)	76973	329.078	415.395	50.000	87.500	375.000
Employees (regressions use the natural log)	76973	11.277	12.014	3.000	6.000	15.000
Corporation	76973	0.694				
Partnership	76973	0.059				
Other Factors:						
Nat'lUnempl	76973	6.099%	1.800%	4.700%	5.600%	7.000%
Nat'lWage ($thou) (regressions use the natural log)	76973	29.403	9.001	20.864	28.356	37.478
SystemicRisk	76973	76,725	107,787	2,926	12,237	141,883
FedFunds	76973	3.108%	2.266%	0.390%	3.260%	5.260%
LinearTrend	76973	121.526	69.125	59.000	122.000	185.000

Table 2: Regression Results for Question (1)

This table focuses on Question (1): Do small banks (still) have comparative advantages in alleviating financial constraints of small businesses? It presents results from OLS regression models in which the dependent variable is *NotSatisfied*, a dummy that equals one if the firm reports that it did not satisfy its borrowing needs and zero 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 variables are defined in Table 1. Time (year-month), industry, industry × time, and state fixed effects are also included where indicated, but not reported. Robust standard errors double clustered by location (see FN 21) and time (year-month) 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)
Dependent Variable:	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*
SmallBankShare	-0.068***	-0.070***	-0.070***	-0.038***
	(-7.47)	(-7.46)	(-7.38)	(-3.32)
Local Market Characteristics:				
Metro	-0.004	0.004	0.004	0.001
	(-0.62)	(0.71)	(0.75)	(0.30)
ln(LocalPopulation)	0.014***	0.016***	0.016***	0.015***
	(4.98)	(6.05)	(6.02)	(6.11)
LocalUnempl	0.536***	0.489***	0.477***	0.540***
	(5.16)	(5.18)	(5.18)	(5.80)
ln(LocalWage)	-0.018***	-0.014***	-0.013***	-0.005
	(-3.01)	(-2.95)	(-2.73)	(-1.43)
Other Local Bank Characteristics:				
EqRat		0.220	0.177	-0.041
		(1.17)	(0.93)	(-0.21)
IlliquidityRat		0.004	0.004	-0.001
		(1.02)	(0.97)	(-0.20)
DepositHHI		0.816	0.810	1.433**
		(1.00)	(0.95)	(2.04)
Branch/Pop		-0.005	-0.006	-0.041*
		(-0.24)	(-0.26)	(-1.87)
FewBanks		0.021***	0.021***	0.007
		(2.91)	(2.86)	(0.99)
Firm Characteristics:				
ExpGenCond		-0.021***	-0.021***	-0.021***
		(-9.68)	(-9.68)	(-9.88)
ExpSales		0.002	0.002	0.002
		(0.92)	(1.11)	(0.93)
ChSales		-0.025***	-0.025***	-0.024***
		(-15.18)	(-14.79)	(-14.69)
ln(Sales)		-0.023***	-0.023***	-0.023***
		(-24.46)	(-24.00)	(-24.25)
ln(Employees)		-0.025***	-0.025***	-0.026***
		(-13.69)	(-14.15)	(-13.90)
Corporation		0.007*	0.006	0.005
		(1.79)	(1.52)	(1.24)
Partnership		0.003	0.003	0.002
		(0.52)	(0.59)	(0.37)
Time FEs	YES	YES	NO	NO
Industry FEs	NO	YES	NO	NO
Industry × Time FEs	NO	NO	YES	YES
State FEs	NO	NO	NO	YES
N	76973	76973	76936	76936
Adjusted R^2	2.15%	6.80%	6.88%	7.15%

Table 3: Robustness Checks for Question (1)

This table presents the results of robustness checks related to Question (1): Do small banks (still) have comparative advantages in alleviating financial constraints of small businesses? Panel A uses a logit specification instead of OLS and shows marginal effects. Panel B splits the sample into metropolitan and rural areas. Panel C uses alternative measures of small bank access. Panel D adds control variables. Panel E uses alternative financial constraint measures. In Panels A-D, the dependent variable is *NotSatisfied*, a dummy that equals one if the firm reports that it did not satisfy its borrowing needs and zero otherwise. In Panel E, the dependent variables are *ExpectedDifficulty*, a dummy that equals one if the firm expects to experience increased financing difficulty in the next three months and zero otherwise; *LoanSpread*, the loan interest rate minus the 3-month Treasury bill yield; and *RateChange*, 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. In every panel, the key explanatory variable is *SmallBankShare*. Panels A-B and D-E define it as the proportion of bank branches within a 50-kilometer radius of the firm that belong to small banks. Panel C uses alternative definitions explained in the panel's header. All variables are defined in Table 1. All the baseline model control variables from Table 2 Column (4) plus industry × time (year-month) and state fixed effects are also included where indicated, but not reported. Robust standard errors double clustered by location (see FN 21) and time (year-month) 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: Logit Estimator	Panel B: Metropolitan versus Rural Areas	
	(1)	(1)	(2)
Estimator:	Logit	OLS	OLS
Sample:	All	Metropolitan	Rural
Dependent Variable:	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*
SmallBankShare	-0.067***	-0.053**	-0.034**
	(-7.06)	(-2.51)	(-2.09)
Baseline Controls	YES	YES	YES
Industry × Time and State FEs	NO	YES	YES
N	76973	41548	35425
Adjusted R^2	6.12%	7.47%	6.27%

	Panel C: Alternative Measures of Small Bank Access					
	(1)	(2)	(3)	(4)	(5)	(6)
SmallBankShare measured using:	3-digit ZIP codes	30-km threshold	100-km threshold	*ln((1+SmallBranch) /LocalPopulation)*	1992 values	3-yr lagged values
Dependent Variable:	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*
SmallBankShare	-0.044***	-0.035***	-0.052***	-0.011***	-0.050***	-0.024**
	(-3.90)	(-3.72)	(-3.07)	(-2.82)	(-5.99)	(-2.05)
Baseline Controls	YES	YES	YES	YES	YES	YES
Industry × Time FEs	YES	YES	YES	YES	YES	YES
State FEs	YES	YES	YES	YES	NO	YES
N	76928	76105	76936	76763	69847	69847
Adjusted R^2	7.17%	7.12%	7.15%	7.16%	6.86%	7.27%

	Panel D: Additional Control Variables			Panel E: Alternative Financial Constraint Measures		
	(1)	(2)	(3)	(4)	(5)	(6)
Additional controls:	Deregulation	Local bank failures	Local house price index			
Dependent Variable:	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*	*ExpectedDifficulty*	*LoanSpread*	*RateChange*
SmallBankShare	-0.039***	-0.036***	-0.040***	-0.047***	-0.119	-0.030
	(-3.33)	(-3.18)	(-3.40)	(-2.63)	(-1.26)	(-1.45)
Baseline Controls	YES	YES	YES	YES	YES	YES
Industry × Time and State FEs	YES	YES	YES	YES	YES	YES
N	76936	76128	76936	51021	44588	54095
Adjusted R^2	7.15%	7.21%	7.18%	11.53%	18.42%	29.95%

Table 4: Simple Approach for Question (2)

This table presents the results of the simple approach to address Question (2): Do small bank comparative advantages change over time? The dependent variable is *SmallBankCompAdv,* plotted in Figure 1 and calculated as the monthly difference between the average *NotSatisfied* of firms with *SmallBankShare* above versus below the sample median for the same month. Explanatory variables include national economic conditions (proxied by *Nat'lUnempl* and *ln(Nat'lWage)*), financial conditions (proxied by *SystemicRisk* and *FedFunds*), and a linear trend. Newey-West standard errors are used to calculate the t-statistics reported in the parentheses. Statistical significance is denoted as ***, **, and * for 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var:	*SmallBank CompAdv*	*SmallBank CompAdv*	*SmallBank CompAdv*	*SmallBank CompAdv*	*SmallBank CompAdv*	*SmallBank CompAdv*
Nat'lUnempl.	-1.399***					-1.865***
	(-8.11)					(-3.66)
ln(Nat'lWage)		0.220***				0.014
		(5.88)				(0.30)
SystemicRisk			-0.008***			-0.000
			(-3.22)			(-0.10)
FedFunds				0.007**		-0.004
				(2.58)		(-1.29)
LinearTrend					-0.000	-0.000
					(-1.54)	(-0.13)
N	221	221	221	221	221	221
Adjusted R^2	25.72%	17.80%	12.49%	11.51%	5.90%	26.32%

Table 5: Alternative Approach for Question (2)

This table presents the results of an alternative approach to address Question (2): Do small bank comparative advantages change over time? This approach adds *SmallBankShare* interacted with economic and financial market conditions as well as a linear trend to the pooled regression model of Equation (1). The dependent variable is *NotSatisfied*, a dummy that equals one if the firm reports that it did not satisfy its borrowing needs and zero otherwise. Explanatory variables include *SmallBankShare* interacted with national economic conditions (proxied by *Nat'lUnempl* and *ln(Nat'lWage)*), financial conditions (proxied by *SystemicRisk* and *FedFunds*), a linear trend, and local economic conditions (proxied by *LocalUnempl* and *ln(LocalWage)*). All the baseline model control variables from Table 2 Column (4) plus industry × time (year-month) and state fixed effects are also included, but not reported. Column (8) also controls for the average values of the local economic conditions over the sample period (level and interacted with *SmallBankShare*), but not reported. The uninteracted aggregate factors are subsumed by the industry × time fixed effects. Continuous variables are mean-centered prior to calculating interaction terms to minimize the influence of multicollinearity (Wooldridge, 2010). The variables used are defined in Table 1. Robust standard errors double clustered by location (see FN 21) and time (year-month) are used to calculate the t-statistics, which are displayed in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*
SmallBankShare	-0.040***	-0.037***	-0.041***	-0.042***	-0.040***	-0.036***	-0.029**	-0.031**
	(-3.50)	(-3.28)	(-3.40)	(-3.58)	(-3.38)	(-3.07)	(-2.45)	(-2.57)
SmallBankShare × Nat'lUnempl	-2.822***					-4.135***	-3.270***	-2.430***
	(-8.80)					(-6.32)	(-4.99)	(-3.47)
SmallBankShare × ln(Nat'lWage)		0.507***				0.001	0.037	0.075
		(7.00)				(0.01)	(0.41)	(0.81)
SmallBankShare × SystemicRisk			-0.000***			0.000	0.000	-0.000
			(-3.92)			(0.21)	(0.03)	(-0.13)
SmallBankShare × FedFunds				0.013***		-0.006	-0.006	-0.006
				(4.76)		(-1.29)	(-1.26)	(-1.24)
SmallBankShare × LinearTrend					-0.000	0.000	0.000	-0.000
					(-1.25)	(0.50)	(0.01)	(-0.61)
SmallBankShare x LocalUnempl							-0.702**	-1.429***
							(-2.35)	(-3.46)
SmallBankShare x ln(LocalWage)							0.028**	0.047**
							(2.23)	(2.52)
Baseline Controls	YES	YES	YES	YES	YES	YES	YES	YES
Industry × Time and State FEs	YES	YES	YES	YES	YES	YES	YES	YES
Avg Local Economic Conditions	NO	NO	NO	NO	NO	NO	NO	YES
SmallBankShare × Avg Local Economic Conditions	NO	NO	NO	NO	NO	NO	NO	YES
N	76936	76936	76936	76936	76936	76936	76936	76936
Adjusted R^2	7.25%	7.22%	7.18%	7.18%	7.15%	7.25%	7.28%	7.29%

Table 6: Regression Results for Question (3)

This table focuses on Question (3): Do small banks also have comparative advantages in providing liquidity insurance to displaced customers of large banks experiencing liquidity shocks during financial crises? It presents results from OLS regression models over the August 2006 – February 2010 sample period. The dependent variable is *NotSatisfied*, a dummy that equals one if the firm reports that it did not satisfy its borrowing needs and zero otherwise. ABCP banks are defined to be those whose holding company's ratio of total ABCP exposure to equity capital is above 40%. *HighABCPExposure* is alternatively measured using a continuous measure (Column (1)) and a dummy measure (Column (2)). The continuous measure is the proportion of branches belonging to ABCP banks within a 50-km radius of the firm. The dummy measure is a dummy based upon whether the continuous measure is above the 80th percentile. $CRISIS^{ABCPMktShock}$ is a dummy that equals one from August 2007 through September 2008, and zero otherwise. $CRISIS^{GeneralMktShock}$ is a dummy that equals one from October 2008 through February 2010, and zero otherwise. The variables of interest are the two triple interaction terms which capture how the effects of *SmallBankShare* on *NotSatisfied* differ for small businesses in markets with high ABCP market exposure during the two shock periods. All the baseline model control variables from Table 2 Column (4) plus industry × time (year-month) and state fixed effects are also included, but not reported. Robust standard errors double clustered by location (see FN 21) and time (year-month) 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)
HighABCPExposure Specification:	Continuous	Dummy
Dependent Variable:	*NotSatisfied*	*NotSatisfied*
SmallBankShare	-0.050	-0.013
	(-1.21)	(-0.34)
HighABCPExposure	-0.350***	-0.087**
	(-3.57)	(-2.48)
SmallBankShare × *HighABCPExposure*	0.650**	0.183**
	(2.01)	(1.99)
Crisis Interaction Terms, using ABCP Market Shock		
SmallBankShare × $CRISIS^{ABCPMktShock}$	0.072	0.029
	(1.58)	(0.86)
HighABCPExposure × $CRISIS^{ABCPMktShock}$	0.422***	0.130***
	(3.07)	(2.96)
SmallBankShare × *HighABCPExposure* × $CRISIS^{ABCPMktShock}$	-1.224***	-0.470***
	(-3.11)	(-3.13)
Crisis Interaction Terms, using General Market Shock		
SmallBankShare × $CRISIS^{GeneralMktShock}$	-0.031	-0.094***
	(-0.79)	(-2.71)
HighABCPExposure × $CRISIS^{GeneralMktShock}$	0.522***	0.108**
	(3.57)	(1.98)
SmallBankShare × *HighABCPExposure* × $CRISIS^{GeneralMktShock}$	-1.006**	-0.215
	(-2.27)	(-1.29)
Baseline Controls	YES	YES
Industry × Time and State FEs	YES	YES
N	29964	29964
Adjusted R^2	11.18%	10.99%

Table 7: Robustness Checks for Question (3)

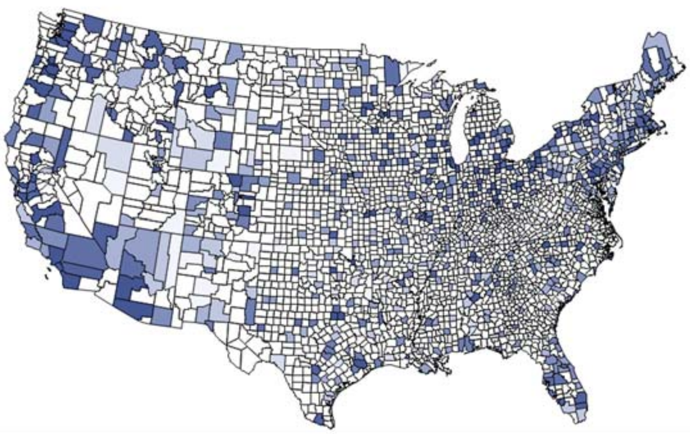
This table presents the results of robustness checks addressing Question (3): Do small banks also have comparative advantages in providing liquidity insurance to displaced customers of large banks experiencing liquidity shocks during financial crises? It presents results from OLS regression models over the August 2006 – February 2010 sample period. The dependent variable is *NotSatisfied*, a dummy that equals one if the firm reports that it did not satisfy its borrowing needs and zero otherwise. ABCP banks are defined to be those whose holding company's ratio of total ABCP exposure to equity capital is above 40%. *HighABCPExposure* is alternatively measured using a continuous measure (Columns (1) and (3)) and a dummy measure (Columns (2) and (4)). The continuous measure is the proportion of branches belonging ABCP banks within a 50-km radius of the firm. The dummy measure is a dummy based upon whether the continuous measure is above the 80th percentile. $CRISIS^{ABCPMktShock}$ is a dummy that equals one from August 2007 through September 2008, and zero otherwise. $CRISIS^{GeneralMktShock}$ is a dummy that equals one from October 2008 through February 2010, and zero otherwise. Columns (3) and (4) exclude the branches of banks with ABCP exposure from the calculation of *SmallBankShare*. The baseline model control variables from Table 2 Column (4) plus industry × time (year-month) and state fixed effects are also included, but not reported. The specifications also include controls for the percentage of branches belonging to failed banks in the past year in the local area and the house price index for the local area (not reported). Robust standard errors double clustered by location (see FN 21) and time (year-month) 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)
SmallBankShare Specification:	Standard	Standard	Excluding Branches of Non-ABCP banks	Excluding Branches of Non-ABCP banks
HighABCPExposure Specification:	Continuous	Dummy	Continuous	Dummy
Dependent Variable:	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*	*NotSatisfied*
SmallBankShare	-0.068	-0.032	-0.052	-0.026
	(-1.63)	(-0.83)	(-1.24)	(-0.70)
HighABCPExposure	-0.322***	-0.075**	-0.272**	-0.051
	(-3.56)	(-2.19)	(-2.56)	(-1.35)
SmallBankShare × High*ABCPExposure*	0.534*	0.140	0.286	0.028
	(1.89)	(1.62)	(1.07)	(0.30)
Crisis Interaction Terms, using ABCP Market Shock				
SmallBankShare × $CRISIS^{ABCPMktShock}$	0.086**	0.044	0.085*	0.045
	(1.97)	(1.37)	(1.87)	(1.36)
HighABCPExposure × $CRISIS^{ABCPMktShock}$	0.415***	0.126***	0.428**	0.123**
	(2.95)	(2.71)	(2.56)	(2.44)
SmallBankShare × High*ABCPExposure* × $CRISIS^{ABCPMktShock}$	-1.200***	-0.460***	-1.004**	-0.347***
	(-3.01)	(-2.94)	(-2.51)	(-2.59)
Crisis Interaction Terms, using General Market Shock				
SmallBankShare × $CRISIS^{GeneralMktShock}$	-0.011	-0.074**	-0.021	-0.077**
	(-0.26)	(-2.02)	(-0.48)	(-2.04)
HighABCPExposure × $CRISIS^{GeneralMktShock}$	0.480***	0.089*	0.435***	0.069
	(3.67)	(1.74)	(2.82)	(1.21)
SmallBankShare × High*ABCPExposure* × $CRISIS^{GeneralMktShock}$	-0.847**	-0.156	-0.572	-0.057
	(-2.20)	(-1.01)	(-1.46)	(-0.36)
Baseline Controls	YES	YES	YES	YES
Industry × Time and State FEs	YES	YES	YES	YES
Local Bank Failures and Local House Price Index	YES	YES	YES	YES
N	29964	29964	29964	29964
Adjusted R^2	11.09%	11.04%	11.08%	11.03%

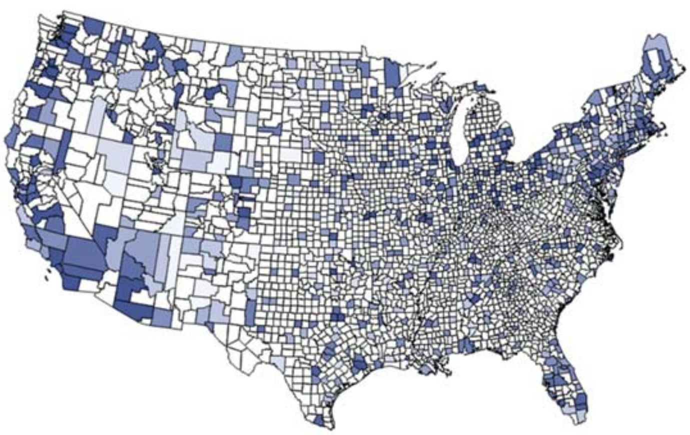
Appendix Figure A.1. Geographical Description of Sample Firms and *SmallBankShare*

Panel A presents the geographical density of our sample firms over the entire sample period (1993-2012) by county, while Panels B and C present similar information for the first and second halves of the sample period, 1993-2002 and 2003-2012, respectively. Panel D shows population by county. In these panels, darker shades indicate greater density. Panel E plots *SmallBankShare* values averaged over the entire sample period by county. In this panel, darker shades indicate higher values (greater proportion of small bank branches).

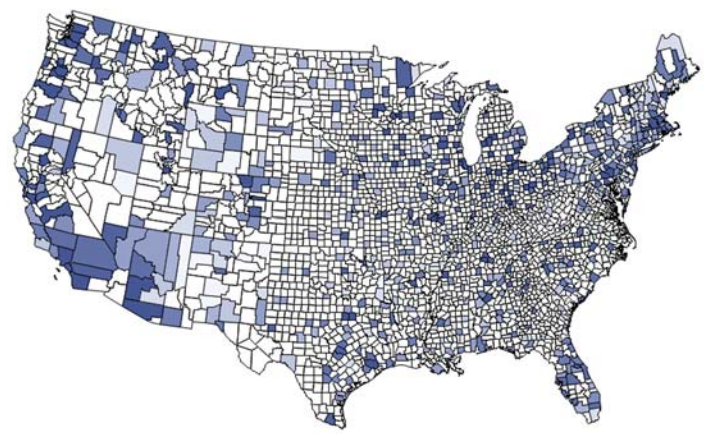
Panel A: Sample Firms by County
(Darker is Denser)



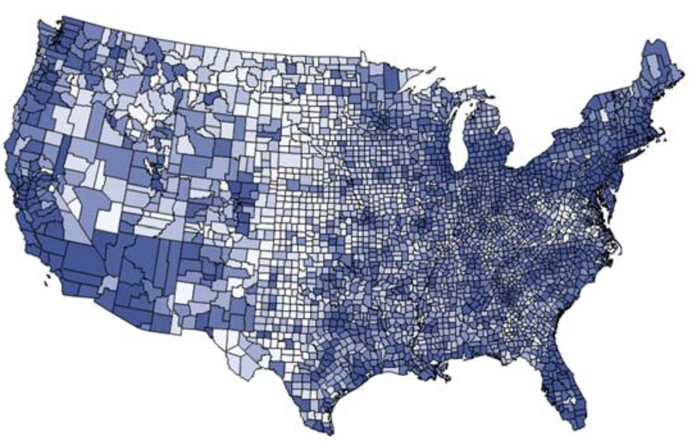
Panel B: Sample Firms by County from 1993-2002
(Darker is Denser)



Panel C: Sample Firms by County from 2003-2012
(Darker is Denser)



Panel D: Population by County
(Darker is Denser)



Panel E: *SmallBankShare* by County
(Darker is Higher Values)