Unexpected Gains: How Fewer Community Banks Boost Local Investment and Economic Development

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Our research examines the impact of dwindling community bank numbers on community investment and economic development. Initially, we confirm the vital role of community banks' small business lending in local development. Contrary to popular belief, we find that a decrease in the number of community banks has a positive impact on community investment through increased small business loan (SBL) originations. Key factors include the local presence of other community banks and the continuity of the consolidating bank's presence. Interestingly, while there is no differential effect in underserved or distressed counties, the effect diminishes when a large bank acquires a community bank without maintaining a local presence. Post-consolidation, community banks emerge larger and more robust, capable of issuing larger SBLs, while larger banks and Fintech firms contribute by providing smaller SBLs. Overall, our findings reinforce the critical contribution of community banks to local development, suggesting that a reduction in their numbers leads to a stronger, more stable banking infrastructure in the small business lending landscape.

Key words: Community development, community investment, community banks, bank consolidation, small business lending

JEL: G20, G21, G28

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1. Introduction.

The focus on banks by researchers and policy makers in recent years has been overwhelmingly on large banks due to their relative asset size. Yet, community banks[1] are typically more focused on community development and are a key catalyst for overall economic growth and account for 97% of all banks in the U.S. in 2019. Over the past couple of decades there has been a steady decline in the number of these community banks due to consolidations and failures, which has ignited a concern that the disappearance of these institutions could signify the loss of an important driver of community development (see, for example, Berger and Udell, 1995; Stein, 2002, and Levine, Lin, Peng, and Xie, 2020). Community banks, which invest a higher percentage of their loan portfolio in SB lending than large banks (Berger, Kashyap, and Scalise, 1995; Strahan and Weston, 1998), have been instrumental for job creation and community development. Brown and Earle (2017), using Small Business Administration (SBA) loan data, show that there are 3-3.5 jobs created with each $1 million loan to a small business. In addition, the U.S. SBA Office noted that, "small businesses have accounted for 66 percent of employment growth over the last 25 years."[2] Given their importance for economic development, the decline in the number of community banks could adversely affect small businesses, which is politically sensitive. In a letter to bank regulators, the Chairman of the U.S. Senate Committee on Banking wrote "Consolidation also harms small businesses. Study after study has documented how, following bank mergers, small business lending dries up and available loans become more expensive. Consolidation among banks also supports consolidation in non-financial industries, undermining small enterprises."[3]

These concerns motivate the key question explored in this study: whether the reduction in the number of community banks leads to a decrease in small business (SB) lending, which in turn could have adverse effects on community investment and economic development. To examine this question, we first investigate the impact of small business loan (SBL) originations on community economic development, and then analyze

[1] Banks with assets below $10 billion that typically serve a small geographic region.
[2] Small Business Facts: Small Business Job Creation (sba.gov)
[3] Brown Urges DED and OCC to Scrutinize Bank Mergers
https://www.brown.senate.gov/newsroom/press/release/sherrod-brown-fed-occ-scrutinize-bank-mergers

how the loss of a community bank affects local SBL originations in counties in which the closed community bank had a physical presence (a full-service branch).

The Federal Reserve Board generally defines community banks as banks that serve a small geographic region with assets below $10 billion. We adopt a similar but simpler definition, considering any commercial bank with assets under $10 billion (in 2019 US dollars) as a community bank and defining a community as a county. Between 1999 and 2019, the aggregate number of community banks substantially decreased by nearly 48%, going from 8,361 to 4,355 (see Figure 1). Despite this steady decline, the proportion of SBLs in their lending portfolios increased slightly from 18.4% in 1999 to 19.2% in 2019, suggesting the decline does not negatively impact the lending focus of these banks on local community development

The importance of the link between local lending and overall economic growth was codified through the Community Reinvestment Act (CRA) of 1977 based on the belief that local bank investment, through lending to small businesses, will lead to faster community development in the local market and this is particularly important for distressed or underserved communities (see e.g., Ding, Lee and Bostic (2018)). An important attribute of the CRA for this study, is the requirement that banks above a certain size cut-off must report SB lending in the local community. This lending focus by community banks is due to their advantage, relative to large banks, in relationship lending on which small firms rely (e.g., Berger and Udell, 1995, 2002; Berger, et al. 2005; Cole, Goldberg, and White, 2004; Berger, Bouwman and Kim, 2017).

We begin our analysis by first examining the impact of SBL originations on community development to establish whether there is in fact a direct link between bank lending and community development, which is at the core of the alarm at the loss of community banks. Originating loans is the mechanism through which community banks invest in small businesses, which is believed to be vital for community economic development. We use three proxies for community economic development: the annual growth in 1) *Small establishments* (number of firms with fewer than 50 employees); 2) *Employment* (the total employment in the county), and 3) *Small firm employment* (employment in the county by firms with fewer than 50 employees). To address potential endogeneity concerns, we use a Bartik-like instrumental variables as in Bartik (1991) and Blanchard and Katz (1992). The results show that the growth in SBL originations is positively associated with measures of community economic development. The positive results remain in distressed and underserved counties and establish a baseline assumption that growth in SBL originations is important for community development. This supports the general belief that local SBL supports local community development which support overall economic development.

As previously discussed, concerns about the loss of community banks are driven by the potential adverse effects of the loss of small banks on community development. Therefore, we next directly examine the impact of the loss (closure) of a community bank on local SBL originations, measured using the CRA data for reporting banks aggregated at the county-year level along with several other data sources that provide detailed county level macro-economic data and bank level information over the 1999 to 2019 sample period. We stop our sample in 2019 to eliminate any potential confounding factors related to the COVID-19 pandemic that may have affected banks' SB lending activity. We use a stacked difference-in-differences (DiD) regression cohort approach where the treatment group consists of counties that experience the loss (closure) of a community bank in a given year. Surprisingly, the results show that counties that lose a community bank experience higher SBL originations after the bank's closure, relative to the control group. Since the CRA data are only available for a subset of banks, given the reporting threshold, in additional tests, the results are supported when we include SBA 7A loan originations for non-CRA reporting banks to capture total SBL originations in a county.

The positive association we uncover is inconsistent with the conventional belief that the loss of a community bank will have adverse effects on community development because of small firms' reliance on community banks for financing. Therefore, we next investigate potential explanations for this counterintuitive result based on popular belief.

Before developing potential explanations, we note that bank closures have been steady over the sample period and are widespread nationally but there are differences in the numbers across counties (see Figure 2) that could affect baseline merger activity. We thus examine county characteristics that affect the probability of a county losing a community bank and its impact on SB lending.[4] This analysis shows that the likelihood of

[4] Note, we use SB lending and SBL originations interchangeably.

losing a community bank is lower in counties with higher deposit concentration and a higher proportion of small establishments, while counties with faster population growth, higher average wages, larger shares of deposits by the top four banks and banks with weaker asset quality are more likely to lose a community bank. Additionally, closures are more likely in underserved or rural counties and those with higher concentration of community bank deposits but are less likely in distressed counties. This analysis implies that county level characteristics play an important role in the reduction of the number banks and possibly its impact on SB lending.

We next examine plausible explanations for this counterintuitive baseline result based on county level characteristics, bank-level decisions and the evolution of SB lending behavior. At the county level, we document that community bank losses lead to increases in SBL originations but only in counties with a high concentration of other community banks. Assessing bank-level characteristics of the entity taking over the closed bank, we find that when the consolidated entity maintains a presence in the local county post-consolidation, there is a significant increase in SBL originations. However, the increase in SB lending is significantly reduced when the new consolidated entity is a large bank (assets >$10 billion). Interestingly, we also find a significant increase in SB lending by other community banks in the county after a community bank closure, highlighting competition as an important driver of the observed results.

To gauge the importance of changes in overall SB lending for the main results, our analysis explores the evolving SB lending practices of community banks, large banks, and the role of Fintech companies. Despite an increase in community banks' asset size during the study period, their proportion of outstanding SBLs within loan portfolios has remained steady, indicating that even as they expand in size, these banks consistently support small businesses. Within the sample period, community banks began originating larger SB loans. Meanwhile, technological advancements in lending have allowed larger banks to increasingly focus on smaller SBL originations and lending to small firms. This outcome is supported by Black and Kowalik (2016) who argue that this may be driven by competition between large and small banks with the growth in lending technologies allowing larger banks to better compete for the smallest loans.

To provide additional insight for our base result, we examine SB lending changes by the consolidated banks in the counties where the closed banks had the highest deposit concentration prior to closure.[5] We create bank-level cohorts at the target county-consolidation year, collecting SB lending and financial data for the proforma consolidated banks (treated) and for other local banks (control) banks within a seven-year window around each consolidation event. Our findings reveal a notable post-consolidation increase in SB lending by the consolidated bank relative to the control group, especially in counties with a larger concentration of other community banks. The effect is less pronounced when the consolidated entity is a large bank. These results suggest that increased size and stability of community banks following consolidation can enhance SB lending in affected counties, challenging the concerns about the negative impact of consolidations on local SB lending.

In addition, during our sample period, the GFC had important effects on the overall banking sector. Interestingly, we find that post-GFC, the increase in SBL originations following community bank closures is primarily driven by community banks, aligning with arguments emphasizing significant structural changes in the banking sector post-GFC that are yet to be fully understood. An emerging factor is the rise in Fintech lending activity in the post-GFC period (Gopal and Schnabl, 2022). Incorporating Fintech lending presence in our analysis, despite the reduced sample size due to data constraints, shows an increase in SBL originations post-community bank closure, supporting the findings by Gopal and Schnabl (2022) and highlighting the evolving landscape of SB lending. Given the influence of Fintech firms, bank lending technology and the GFC, it is not possible for us to disentangle the effects of these events on the aggregate post-GFC results.

Given the importance of community banks to the overall economy, it is surprising that there have been few studies that examine the importance of community banks on community development through the provision of capital to small firms. The existing literature has focused on large banks' importance for the overall economy, except for studies that assess the importance of Fintech lending to small firms (see e.g., Gopal and Schnabl, 2022). The more recent related literature has focused on relationship lending to these firms and their potential importance, especially during a crisis, (see e.g., DeYoung, Grom, Torna, and Winton, 2015, and Levine, Lin and Xie, 2021). There are a few papers that examine the changing banking landscape driven

[5] The mean (median) fraction of deposits held by closed banks in their main county is 82.3% (99.9%).

by macroeconomic events and the evolution of banking strategies. Kundu, Muir and Zhang (2024) show that banks have evolved strategies based on deposits rates, which leads to differing approaches to risks in lending driven by technological advancements.

Surprisingly, there is little finance research on a very important aspect of the U.S. economy, community development. Community banks play a vital role in community development and job creation that is generally not the main focus of large banks' lending strategy. Community economic development is a key factor that drives the growth and stability of any economy. The results of this study make important contributions in the understanding of important drivers of community investment, job creation and overall economic growth. Our findings underscore the impact of community banks on local economic development through their SB lending activity. Furthermore, our results show that the financial stability and concentration of these institutions in the local community, and not the aggregate number, will drive future growth in SBL originations and community development.

The paper is organized as follows. Section 2 describes the data and sample selection. Section 3 discusses the role of community banks in community economic development and the effect of losing of a community bank on county-level SB lending. Section 4 examines explanations for the rise in county-level SB lending following community bank closures. Fintech lending presence is addressed in both sections 3 and 4. Section 5 investigates consolidated bank-level SB lending in the counties of bank closures. Section 6 discusses the impact of the GFC on SB lending by community banks and examines robustness of our findings. Section 7 concludes.

2. Data and sample description

We begin by obtaining data on all bank closures from the Federal Deposit Insurance Corporation's (FDIC) Research Information System (RIS) merger database and from the FDIC's Failed Banks list. The merger database identifies all closed institutions and tracks the merger history of all active and inactive FDIC-insured institutions as of a given quarter. The FDIC's RIS merger database includes the closing date for closing institutions with the following outcomes: merged with assistance; absorption with assistance, or partial purchase and assumption with assistance. We obtain information on failed institutions in which there was no acquirer involved from the FDIC's list of failed institutions. We identify the closing date, location, and transaction details for all commercial banks (entity type 10) with a closing date between 1999 and 2019. We exclude deals involving banks operating outside of the 50 U.S states or the District of Columbia. Our final sample consists of 5,769 commercial bank closures during our sample period, including 5,640 community banks.

We group bank closures into two broad categories: 1) *Merger/consolidation* – for closing institutions with a transaction code of 221 (Absorption), 222 (Consolidated), or 223 (Merger),[6] and 2) *Failure* – for institutions that failed.[7] In our sample, we have 5,291 (5,164) total (community bank) *Merger/consolidations* and 478 (476) total (community bank) failures. We note that in most bank failures, a new entity takes over primarily in an assisted absorption. Our sample includes only 20 bank failures (out of 478) in which there is no new entity (acquirer) involved.

We proceed to identify the loss of a bank in a county using data from FDIC's Summary of Deposits (SOD) database. Specifically, for our sample of bank closures, we identify all counties in which those banks had a physical presence (defined as a full-service branch) in the last year of their existence.[8] Next, we construct an indicator variable, *Loss of bank*, which equals one for county c in year t if one or more banks with a presence in year t no longer operate in the county in year $t+1$. We focus on community banks, which could be more important in fostering community development at the local level through SB lending because of their advantages in relationship lending.

To assess how the loss of community banks affects community investment through the impact on SB lending, we next compile data on SBL originations by financial institutions from the Disclosure Reports in the FFIEC's Community Reinvestment Act (CRA) database that provides detailed data on loan originations by reporting institutions. Specifically, all state member banks, state nonmember banks, national banks, and savings associations with assets more than an annually established threshold (roughly $1 billion in constant

[6] We use "CODE2XX" from the FDIC's RIS merger database to classify bank closings by type.
[7] Failures include transaction codes (CODE2XX) of 211 (Absorption- assisted) and 215 (Partial purchase or assumption – assisted), as well as failed banks where there was no acquirer involved, based on the FDIC's Failed Banks list.
[8] Using the FDIC's SOD database, we focus on banks with branches with code (BRSERTYP) of 11 or 12 [Full service, brick and mortar, and Full service, retail office]. SOD data is collected as of June 30th of each year.

2005 dollars) for both the prior two calendar years are subject to the data collection and reporting requirements of the CRA. We obtain data on lending from the CRA database for all reporting institutions.[9] We proceed to aggregate SBL originations across all reporting institutions at the county-year level and use this measure, *SBL originations*, as our main proxy of local community investment. In addition, we use two other proxies for local community investment: *SBL originations to small firms* and *Total SBL originations*. *SBL originations to small firms* are the aggregate data on SBL originations to firms with less than $1 million in sales from the FFIEC's CRA database. *Total SBL originations* incorporate SB lending in a county by non-CRA reporting banks by adding the aggregate Small Business Administration (SBA) 7A loans data for those banks to the *SBL originations* measure at the county-year level.

We obtain information on county-level measures of employment, population, and additional business conditions from the Bureau of Economic Analysis, the U.S. Census' County Business Patterns (CBP), the U.S. Census Bureau Small Area Income and Poverty Estimates (SAIPE), U.S. Bureau of Labor Statistics (BLS) Local Area Unemployment Statistics, and the Federal Housing Finance Agency. We assess the impact of the loss of community banks in poor and underserved areas by classifying counties as distressed or underserved, following the regulatory agencies' criteria to identify such areas. Specifically, a *Distressed* county is one that meets one or more of the following criteria: 1) unemployment rate > 1.5 times the national unemployment rate; 2) Poverty rate >=20%; 3) Population loss greater than or equal to 10% from the previous to the most recent decennial census. Similarly, an *Underserved* county is one with an urban influence code of 7, 10, 11, or 12, as defined by the Economic Research Service of the U.S. Department of Agriculture.[10] Underserved counties tend to be more rural and less densely populated than other counties. Finally, financial data are from the quarterly

[9] The CRA database has information from various financial institutions, including banks, savings and loans, trust companies, industrial loan companies, and consumer nonbanks. In our main analyses, we aggregate SBL originations across all reporting institutions. In additional tests, we aggregate SBL originations by type, including community banks and large banks (commercial banks with assets >$10 billion).
[10] Specifically, underserved counties include UIC codes 7: Noncore adjacent to a small metro and does not contain a town of at least 2,500 residents;10: Noncore adjacent to micro area and does not contain a town of at least 2,500 residents; 11: Noncore not adjacent to a metro/micro area and contains a town of 2,500 or more residents, and 12: Noncore not adjacent to a metro/micro area and does not contain a town of at least 2,500 residents.

Call Reports from March 1999 through December 2019, obtained from the FDIC's RIS financial time series (FTS) database. Appendix A provides descriptions of all variables used in the analyses.

Our final county-level panel dataset consists of 3,151 counties, out of which 89.8% (85.8%) experienced the loss of a bank (community bank). Figure 1 displays the distribution of the sample of community bank closures by year and by type. Most community bank closures (91.6%) during our sample period are a result of mergers/consolidations. Figure 1 shows that the reduction in the number of community banks began well before the GFC and continues throughout our sample period. Community bank failures are rare until the GFC, reaching a peak of 128 in 2010.

Figure 2 is a heat map of community bank closures across counties over the sample period. The figure shows that bank closures are spread across the country but there are counties that experienced more closures than others, but they are not concentrated in any particular region of the country. Community development, or activities that revitalize or stabilize distressed or underserved areas, may be affected by the decline in the number of community banks resulting from consolidations that could lead to changes in lending to small and local firms. Thus, later in the paper we assess the implications of bank consolidations on SB lending, with particular focus on the effect in distressed and underserved counties.

Table 1 reports descriptive statistics of the main variables used in our analyses at the county-year level. The table includes our measures of community development and our main measures of community investment. The mean value of *SBL originations* across county-years is $23.2 million. The mean amount of *SBL originations to small firms* is $10.4 million, and that of *Total SBL originations*, which, as noted, includes the aggregate SBA 7A loan originations by non-CRA banks, is $24.1 million.[11]

[11] From Table 1, *Ln (SBL originations)* is 10.054. Thus, the average amount of SBL originations is $23,247,595 [(exp$^{10.054}$ -1)*$1,000]. Similarly, the average amount of *SBL originations to small firms* is $10,393,166 [(exp$^{9.249}$ -1)*$1,000], and the average amount of *Total SBL originations* is $24,099,792 [(exp$^{10.090}$ -1)*$1,000]. We use the natural log of one plus SBL originations because there are zeros in the data for loan originations by size and for loans to small firms.

3. Community investment, community development and the loss of community banks

The focus on community banks for community development is based on the idea that access to capital is important for economic development. To examine the importance of local community banks for community investment, we first investigate whether SB lending is associated with community development in section 3.1. Having established a positive impact in section 3.1, we examine whether the loss of community banks in the local market impacts community investment in section 3.2.

3.1. Does community investment have an effect on community economic development?

As noted in the introduction, an important belief held by politicians and policy makers is that small businesses are key to economic growth. These firms typically borrow from community banks,[12] which extant research has shown to have advantages in lending to small businesses through relationship lending (see. e.g., Berger and Udell, 1995, 2002; Berger, et al. 2005; Cole, Goldberg, and White, 2004; Berger, Bouwman and Kim, 2017).[13]

In our analysis we use SBL originations as a one proxy for direct community investment in small businesses. In Table 2, we examine how the growth in *SBL originations* affects community development using three proxies for community economic development, which include the annual growth in: 1) *Small establishments*– number of firms with fewer than 50 employees; 2) *Employment* –the total employment in the county, and 3) *Small firm employment*– the employment in the county by firms with fewer than 50 employees. Using these measures, we run several specifications of the following model:

$$\Delta Y_{ct} = \alpha + \beta_1 \, \Delta Ln(SBL\ originations)_{c,t-1,t} + \mathrm{Z}_{c,t-1} + \gamma_c + \delta_t + \varepsilon_{j,t} \tag{1}$$

$\Delta Y_{c,t}$ refers to our proxies for community development, measured as the change from *t-1* to *t* in the natural logarithm of: *Small establishments, Employment*, or S*mall firm employment*; $\Delta Ln(SBL\ originations)_{c,t-1,t}$ is the change in the natural log of (1 + SBL originations) in county *c* from *t-1* to *t*. $Z_{c,t-1}$ is a vector of county-level

[12] During the 1999 to 2019 period, for the average community bank, over 53% of its SBL originations are to small firms (See Berger and Black (2019) for a review of the literature).
[13] Berger, Goulding, and Rice (2014) argue that improvements in technologies and deregulation in the banking industry may contribute to narrowing the advantages of community banks in using soft information and building relationships with small, opaque firms.

controls that includes *Population growth,* the annual growth in the county's population; *Ln(average wages)* – natural log of the average real wages; *Growth in per capita personal income* – the growth in per capita income, and *Change in HPI(%)*– annual change in the housing price index. We include county fixed effects (γ_c) to control for time invariant county differences and year fixed effects (δ_t) to control for changes in macroeconomic conditions and technology over time. Standard errors are clustered at the county level.

One concern with using OLS regressions to estimate equation (1) is that omitted factors may affect both SB lending activity and community development. For example, it could be argued that banks increase SB lending activity in counties experiencing higher growth, suggesting a form of reverse causality that complicates the interpretation of our findings as causal. To address these endogeneity concerns, we instrument *ΔLn(SBL originations)* using a Bartik-like instrumental variable (Bartik, 1991; Blanchard and Katz, 1992; Goldsmith-Pinkham, Sorkin, and Swift, 2020). The approach uses as an instrument for SBL origination growth at the county level the (predetermined) share of deposits in each county by community banks and large banks times the aggregate growth in SBL originations for banks in each size group at the national level. Specifically, our Bartik instrument for *ΔLn(SBL originations)* is constructed as follows:

$$Bartik_{ct} = \sum_k w_{cs} g_{ts} \tag{2}$$

w_{cs} is county *c*'s share of deposits held by banks in size group *s* before the beginning of our sample period (as of 1998);[14] *s* denotes the two bank size groups: *Community* (<$10B) and *Large* (>$10B). g_{ts} is computed as the aggregate *ΔLn(SBL originations)*, where SBL originations are aggregated across all banks in size group *s* *outside* the state in which county *c* is located. We exclude the county's own state in the computation of the aggregate *ΔLn(SBL originations)* to avoid capturing trends in loan growth that may be correlated with county or state-wide conditions.

We present first- and second-stage results from the estimation of equation (1) using our Bartik instrument in columns (1)-(6) of Table 2. The first- (second-) stage results are shown in the odd- (even-)

[14] We obtain the share of deposits in each county by banks in each size group from the FDIC's SOD database as of June 1998.

numbered columns. First-stage results reveal strong explanatory power of our Bartik instrument. The Sanderson-Windmeijer (2016) multivariate *F*-tests of excluded instruments (*F*-statistics above 30) easily reject the null of weak instruments based on Stock and Yogo's (2005) critical values.

The second-stage results show that the *Instrumented ΔLn(SBL originations)* significantly positively impacts all three proxies for community development. From column (2), a one-standard-deviation increase in the *Instrumented ΔLn(SBL originations)* (0.051) is associated with a 0.0069 increase in *ΔLn(Small establishments)* in a county, which represents a 21.6% increase relative to its standard deviation (0.032).[15] We obtain results of similar magnitudes when we use alternate proxies for community development in columns (4) and (6). Overall, the results confirm that SB lending is a positive catalyst for community economic development through its impact on employment growth and growth in small establishments.

3.2. Does the loss of a community bank impact SB lending?

To investigate the effect of a community bank closure on SB lending (our proxy for local community investment), we use a cohort approach and estimate stacked difference-in-differences (DiD) regressions. We use this approach instead of the standard staggered DiD with two-way fixed effects (TWFE) given the issues associated with the interpretability of the TWFE estimator from staggered DiD (Goodman-Bacon, 2021), as well as the inherent bias associated with the staggered DiD estimates (e.g., Barrios (2021), Baker, Larcker, and Wang (2022)). The stacked DiD approach relies on the use of alternative groups to serve as controls (see e.g., Cengiz et al. (2019), de Chaisemartin and D'Haultfoeuille (2022)). We form treatment cohorts for counties that experience the loss of a community bank in given year, focusing on a narrow seven-year window (*t-3* to *t+3*) around the *Treatment* (community bank closure) year and form cohorts starting in 2002 to ensure we have three years in the pre-treatment period in each cohort. We exclude cases in which the treatment counties experience another bank closure within the event window. For each treatment cohort, the control group consists of counties that do not experience the loss of a bank during our sample period (*Never-treated*) and/or those

[15] 0.0069= (0.136 x 0.051), where 0.136 is the coefficient on the *Instrumented ΔLn(SBL originations)* in column (2) of Table 3 and 0.051 is its standard deviation. 0.216= 0.0069/0.032, where 0.032 is the standard deviation of *ΔLn(Small establishments)*.

counties that have not yet experienced the loss of a bank (*Not yet treated*). We then evaluate the impact of the loss of a community bank on SB lending using the following stacked DiD regression:

$$Ln(SB\ lending)_{c,j,t} = \alpha + \beta_1 Post\ \times\ Treat_{c,j} + \beta_2 X_{c,j,t-1} + \gamma_{c,j} + \delta_{t,j} + \varepsilon_{c,j,t} \tag{3}$$

$Ln\ (SB\ lending)_{c,j,t}$ refers to the natural log of one plus the amount of *SBL originations* (*SBL originations to small firms*) {*Total SBL originations*} in county *c* and treatment cohort *j* in year *t; Post* is an indicator equal to one starting the year after county *c* in treatment cohort *j* loses a community bank and zero otherwise; *Treat* is an indicator equal to one for the county losing a community bank in cohort *j* and zero otherwise. $X_{c,j,t-1}$ is a vector of lagged county-level controls that includes *HFI deposits*; *Loans-to-assets*; *Capital ratio*; *NPL-to-loans*; *% Change in HPI*; *Population growth*; *Ln (average wages)*; *Growth in per capita personal income* and *Share of deposits- top 4 banks*. *Treat* and *Post* are excluded from the estimation because they are subsumed by the fixed effects, which include county-by-treatment cohort ($\gamma_{c,j}$) and year-by-treatment cohort ($\delta_{t,j}$) to control for time invariant differences between treatment and control counties as well as any secular time trends (Gormley and Matsa (2011)). We cluster standard errors at the county-by-treatment cohort levels.

The results from estimations of equation (3) are shown in Table 3. Overall, the results in Table 3 show that SB lending, *Ln(SBL originations)* (*SBL originations to small firms*) {*Total SBL originations*}, is higher in treatment counties in the years after the loss of a community bank relative to the control group. In columns (1)-(3) we use the control group of *Not yet treated* and *Never treated* counties. From column (1), the coefficient on the interaction term, *Post* x *Treat*, indicates that *Ln(SBL originations)* is 0.071 higher in treatment counties following the loss of a community bank, relative to the control group, which represents a 4.2% increase relative to its standard deviation (1.686). The results are slightly larger in magnitude when we focus on *Ln(SBL originations to small firms)* (column (2)). Results are similar when using the broader measure of SB lending activity (*Total SBL originations*) in column (3) that attempts to capture SB lending by non-CRA reporting banks. In columns (4)-(6) we replicate the results in columns (1)-(3) using an alternate control group, *Never Treated*. The results using the alternate control group are similar in magnitude and statistical significance.

An important assumption in using the stacked DiD analysis is the parallel trends assumption. We estimate equation (3) replacing *Post* with timing indicator variables equal to one for years *t-3* through *t+3* around the community bank closure in the treatment county and include interactions between the timing indicator variables and *Treat* to test this assumption. Figure 3 graphs the coefficients on the interaction terms, along with 95% confidence intervals. Consistent with the *parallel-trends* assumption, the figure shows insignificant coefficients on the interaction terms between *Treat* and the pre-treatment indicators variables, with positive and significant coefficients on the interaction terms for the post-treatment indicator variables, suggesting that treatment and control counties follow similar patterns in terms of SBL originations in the pre-period, but the difference becomes significant after treatment.

Another possible concern is that bank closures in a county also may affect our control variables leading to the "bad controls" problem in our stacked DiD analysis (See Angrist and Pischke (2009)). To address this potential concern, we replicate the results using controls as of the year before the closure (t-1) in each cohort, interacted with the indicator *Post.* Un-tabulated results[16] confirm our findings.

In additional results, not tabulated for brevity, we examine the impact of FinTech lending in a county and its effect on SB lending by controlling for the fraction of total SB lending in the county by Fintech firms, using data from Gopal and Schnabl(2022).[17] While the sample is reduced given the data limitations, the results continue to show increases in *Ln(SBL originations)* and *Ln(SBL originations to small firms*) after a community bank closure.

As discussed previously, a small set of the bank closures is due to the failure of a community bank. In most of these cases (all except 20 of our community bank failures), a new entity takes over the failed bank. In un-tabulated results, we examine the importance of the difference in the types of closure. The results show that counties experiencing community bank consolidations have a higher increase in *Ln(SBL originations)* and *Ln(SBL originations to small firms*) after the loss of a community bank relative to the control group. We observe similar results for counties experiencing community bank failures, although the statistical significance of the results for *Ln(SBL originations)* is weaker in some cases. The results show that loss of a community bank is correlated with an increase in SB lending in the county of the community bank loss. In general, the

[16] All un-tabulated results can be found in our Internet Appendix.
[17] We thank Philipp Schnabl for providing access to his county-level small business FinTech lending data. The data covers the period 2006-2016.

aggregate results are counter to conventional beliefs about the effect of the loss of community banks on SBL originations.

4. What explains the increase in community investment post-community bank closures?

The aggregate result that the loss of a community bank is associated with an increase in SBL originations is puzzling based on common beliefs related to the potential impact of the loss of community banks on community economic development. In this section, we examine potential explanations for this result. We first examine whether community characteristics help explain the results since bank success is at least partially affected by local community attributes. Another potential explanation is that the characteristics of the merged entity affect the community lending after community bank closure. In addition, the surprising result could be driven by structural changes in SB lending strategy by community banks driven by market changes.

4.1. How do county characteristics matter for understanding the impact of the loss of community banks?

One of the main concerns raised by policy makers about the reduction in the number of community banks is that certain types of counties may be more adversely affected. Our results show that the reduction in community banks lead to an increase in SB lending, but this could be driven by larger and more developed counties, while counties that are in most need of investment to foster development may experience declines in SBL originations.

As a first step in exploring the drivers of the rise in SBL originations after community bank closures, we examine the characteristics of counties that are more likely to lose community banks. To do so, we use the panel dataset at the county-year level and estimate linear probability models where the dependent variable is *Loss of a community bank*, an indicator variable equal to one if one or more community banks with physical presence in the county in year *t* no longer operate in the county in year *t+1*. In addition to the controls used in Table 3 we include *Small establishments %* and control for counties losing other (large) banks using *Loss of banks >$10B* (See Appendix A for variable definitions).

The results are shown in Table 4. Column (1) shows the baseline specifications. Counties with higher bank deposit concentration, those with a larger share of small establishments, and counties with better capitalized banks are less likely to lose a community bank. In contrast, counties with higher population growth, higher average wages, a larger share of deposits by the big four banks, and with banks with higher non-performing loans have a higher probability of losing a community bank. These results support the idea that there are certain economic county characteristics that are important in predicting the loss of a community bank.

As previously mentioned, the main concerns about the decline in the number of community banks are based on the impact on local development in poorer counties or in those with fewer bank services for small businesses. Importantly, the CRA was created with distressed and underserved counties in mind so that banks would have incentives to invest in such counties to help drive community development. To investigate whether these counties are more likely to lose a community bank, in columns (2) and (3) of Table 4 we add an indicator for *Distressed* and *Underserved* counties, respectively. The results show that *Distressed* counties are less likely to experience the loss of a community bank, while *Underserved* counties are more likely to experience the loss of a community bank. Regulators' focus on distressed counties may explain why such counties are less likely to lose a community bank. Underserved counties are those in more rural areas that tend to have lower bank presence, and the results suggest that bank closures are more likely in such counties, where small business creation opportunities may be scarce.

Lastly, we investigate whether the loss of a community bank is, in part, driven by the concentration of community banks in a county. In counties with a high community bank concentration, consolidation could lead to a more efficient distribution of such banks. In column (4) of Table 4 we include *High deposit share-community banks*, an indicator equal to one for counties in which the share of deposits by community banks is in the top tercile of the distribution in a year and zero otherwise. Results show that counties with ex-ante higher share of community banks are more likely to lose a community bank.

Given certain counties are more likely to lose community banks, we examine whether such county attributes impact the effect of community bank closures on community investment. To assess the importance of the loss of a community bank for *Distressed* and *Underserved* counties, we estimate the stacked DiD regressions in equation (3) including interactions with indicator variables for *Distressed* and *Underserved* counties. We show results in Panel A of Table 5. For brevity, we show results using the baseline control group *(Not yet* and *Never treated*). In columns (1)-(3) we show results using interactions with *Distressed*, while columns (4)-(6) show the interactions with *Underserved* counties.

The results in Panel A of Table 5 show that community bank closures do not have differential effects on SB lending in distressed or underserved counties. The coefficients on the triple interaction terms, *Post* x *Treat* x *Distressed* (*Underserved*) are insignificant across all regression specifications. In contrast, the coefficient estimates on *Post* x *Treat* are positive and statistically significant for *Ln(SBL originations)* and *Ln (Total SBL originations)* indicating that overall, the loss of a community bank leads to increases in SB lending activity across counties that lose a community bank, relative to the control group. We find similar results using the alternate control group (*Never Treated*).

In Panel B of Table 5, we examine the moderating effect of the concentration of community banks in the county, using interactions with *High deposit share–community banks*. Results in Panel B suggest that the presence of community banks in a county is an important factor contributing to the increase in SB lending in counties that experience the loss of a community bank. First, we observe significant positive coefficients on the triple interaction term *Post* x *Treat* x *High deposit share–community banks* across all regression specifications. Importantly, the results show that only those counties with a large presence of community banks experience an increase in SB lending after the loss of a community bank. We find no significant effects in other counties (insignificant coefficient on *Post* x *Treat*). Second, in unreported results we confirm that the increase in *Ln(SBL originations*) and *Ln(SBL originations to small firms*) in counties with *High deposit share–community banks* is driven by lending by community banks and not large banks. The coefficient on the triple interaction term *Post* x *Treat* x *High deposit share–community banks* is positive and significant when using aggregate SB lending activity by community banks in the county, i.e., *Ln (SBL originations)-community banks* and *Ln(SBL originations to small firms)-community banks*. In contrast, the coefficient is negative but insignificant in regressions that use lending activity by large banks.

4.2 How do merged-bank characteristics matter for understanding the effects of the loss of community banks?

As noted, community bank closures are primarily driven by mergers/consolidations and by bank failures, to a lesser extent. But even in bank failures, in most cases, a new entity takes over the failed bank primarily through an FDIC-assisted merger; for simplicity, we refer to the new entities as acquirers, even when they take over a failed bank. In this section, we examine the impact of three characteristics related to the new consolidated entities: the size of the new entity, whether the new entity has a presence in the local county, and the resulting change in SB lending by its competitors in the county.

In Table 6, we examine whether the consolidated entity's size is associated with the subsequent SB lending activity in that county as strategies related to SB lending may be correlated with bank size. The analysis thus excludes the 20 community bank closures where there is no acquirer taking over the failed bank. Table 6 shows the results from the estimation of stacked DiD regressions in equation (3) that includes interactions with an indicator variable, *Large*, which equals one when the acquirer is a large bank (total assets >$10 billion) and zero otherwise.[18] We use the acquirer size as a proxy for the consolidated entity's size because there are only a few cases in which two community banks merge and increase in size to over $10 billion in total assets. Our results are unchanged if we classify these cases as *Large*. Our sample includes 5,620 community bank closures in which a new entity (acquirer) takes over the closed bank. In 4,845 (775) of those bank closures, the new entity is another community (large) bank. There are only 64 cases in which the new entity is also a community bank, but the consolidated entity's size exceeds $10 billion (in constant 2019 US$s).

The results in Panel A of Table 6 reveal that the increase in SB lending activity in counties that lose community banks is driven by deals involving a community bank acquirer. The coefficients on the interaction term, *Post* x *Treat* are positive and statistically significant across all model specifications. In contrast, the results show that the effect is significantly smaller when the acquirer, and hence merged entity, is a large bank

[18] In cases in which a county has more than one community bank closure in the same year, we code *Large* as one if at least one of those community bank closures involves cases in which a large acquirer takes over.

as the coefficient estimates on the triple interaction term, *Post* x *Treat* x *Large*, are negative and statistically significant.

The effects of the loss of a community bank may differ based on whether the new consolidated entity continues to have a presence in the county after the community bank closes. We explore this conjecture by estimating equation (3) using interactions with an indicator variable, *Presence-post closure,* which equals one if the consolidated entity (acquirer) has a physical presence (a full-service branch) in the closed bank's county after closure, and zero otherwise.[19]

We present these results in Panel B of Table 6. Overall, the results show that the *Ln(SBL originations to small firms)* is larger after community bank closures in counties in which the new consolidated entity continues to have a presence in the county after the closure, but we find no differential effects on *Ln(SBL originations)* and *Ln(Total SBL originations)*. The coefficient estimates on the triple interaction term, *Post* x *Treat* x *Presence-post closure* is positive and statistically significant when we use *Ln(SBL originations to small firms)* as a proxy for community investment. In-county presence of the consolidated entity is thus particularly important when assessing the effects on *Ln(SBL originations to small firms).* As column (2) shows, community bank closures do not lead to an increase in SB lending to small firms if the consolidated entity does not remain in the county after the community bank closure (the coefficient on *Post* x *Treat* is insignificant). In addition, in un-tabulated results, we examine whether the effects of in-county presence differ between closures related to mergers/consolidations and failures. Results show that the positive effects associated with consolidated entity's presence in the closed bank's county on SBL originations to small firms is similar in both types of community bank closures, although the magnitude is larger for bank failures.

[19] For counties with multiple bank closures in the same year we code *Presence after* as one if at least one of the community bank closures involves an acquirer that retains a physical branch in the county after the closure.

Overall, the results in Table 6 reveal that the size of the acquiring bank, and hence consolidated entity, and whether the consolidated entity maintains a presence in the county after closure are key factors when assessing the effect of community bank closures on SB lending activity.

To alleviate concerns that our results could be mechanical because we are only able to capture SBL originations of CRA-reporting banks and non-reporting banks originating SBA 7A loans, while many of the bank closures we study involve non-CRA reporting banks not originating SBA 7A loans, we proceed to examine SB lending by other banks in the county by aggregating our proxies for community investment at the county-year level across all banks, excluding lending by the closed entity in the three years before closure as well as any lending by the consolidated entity after the bank closure. We then estimate the stacked DiD regressions in equation (3) using SB lending by other banks as our dependent variable. That is, we use *Ln(SBL originations-other banks), Ln(SBL originations to small firms- other banks)*, and *Ln(Total SBL originations-other banks)* as our explanatory variables. We present the results in Table 7 using the baseline control group (*Not yet* and *Never treated*) for brevity.

The results in Panel A of Table 7 show that other banks in *Treatment* counties increase SB lending activity, relative to the control group, post-community bank closure. The results are both statistically and economically significant. From column (1), results show an increase of 0.092 in *Ln(SBL originations-other banks)* after the loss of a community bank in the county, relative to the control group, which represents a 5.5% increase relative to its standard deviation (1.68). We observe similar results for our other two proxies for community investment.

Our prior results show that the increase in SB lending following community bank closures in a county is driven by counties with a large presence of community banks. We thus examine whether such an increase is driven by the response of other banks in such counties by including interactions with the indicator *High deposit share–community banks.* The results are reported in Panel B of Table 7 and show a significant increase in SB lending by other banks post-closure in counties with more ex-ante community bank presence. In other counties, community bank closures have no effect on SB lending activity by other banks (coefficient on *Post* x *Treat* is insignificant). These results suggest that other local community banks are partially responsible for the observed increase in SB lending activity in counties that lose a community bank. In un-tabulated results, we directly examine this conjecture by replicating results in Panel B of Table 7, separately assessing the SB lending activity by other community banks and by large banks in the county. Results confirm that the increase in SB lending activity post-closure in counties with ex-ante community bank presence is driven by other community banks in the county.

4.3 Did SB lending strategy change for banks?

So far, the results show that the reduction in the number of community banks is associated with an increase in SB lending over the sample period. This result could be driven by an evolution of SB lending as there has been changes in technology and SB lending activity over the past two decades. Berger and Black (2011) argue that hard information-based lending technologies allow large banks to expand lending to small firms. Gopal and Schnabl (2022) using unique data on Fintech lending, show that there is an increase in Fintech lending around the GFC accompanied by increased in SB lending by banks. The results of the study show that Fintech and bank lending increased but maybe in different SB loan types. We examine this idea by focusing on whether the lending strategy of community and large banks changed over the sample period, which has implications for the future of SB lending.

The size of community banks has steadily increased partly as a result of consolidation in the industry. As shown in Panel A of Figure 4, the mean and median size of community banks has almost doubled over the sample period. During this period the distribution of SB loans also evolved differently between large and community banks. Panel B of Figure 4 shows the evolution in SBL origination size over the sample period for large banks and community banks. As shown in Panel B there has been a steady increase in small SBL originations (less than $100k) for large banks as a percentage of total SBL originations, increasing from 27% in 1999 to 46% in 2019. In contrast, for community banks, as a fraction of total SBL originations, small SBL originations declined from 25% in 1999 to 17% in 2019. Conversely, community banks have increased percentage of larger SBL originations ($100k to $1 million) as a percentage of total SBL originations while large banks have decreased larger SBL originations.

To better understand the importance of the increased size of community banks and the change in SB lending by loan size by community and large banks we use the stacked DiD cohort approach and estimate equation (3) using *Ln(SBL originations)*, *Ln(SBL originations to small firms)*, and *Ln(SBL originations to other firms)*, aggregated at the county-year level across each type of bank (community and large) as our explanatory variables. We present the results in Table 8 using the baseline control group (*Not yet* and *Never treated*) for brevity. We compute *SBL originations to other firms* as the difference between *SBL originations* and *SBL originations to small firms*. In columns (1)-(3) we show results for community banks while columns (4)-(6) represent results for large banks. The positive and significant coefficients on *Post x Treat* in columns (1) and (4) show that SBL originations by both large and community banks is higher in *Treatment* counties in the years after the loss of a community bank relative to the control group. Importantly, there is no change in *Ln(SBL originations to small firms)* for community banks (Column (2)), while there is a significant increase in *Ln(SBL originations to small firms)* for large banks. Conversely, there is a significant increase in *Ln(SBL originations to other firms)* for community banks and no change for large banks in the county post-community bank closure.

5 Bank-County Level Analysis - SB Lending Activity of the Consolidated Entity.

In section 4, we showed that the impact of community bank closures on SB lending varied based on the characteristics of the merged consolidated entity. In this section, we examine more closely the SB lending activity at the new consolidated bank level. When a closed bank is taken over by a new entity, the consolidated bank may be financially stronger and able to fund more SB loans, which may partly explain our results. In addition, as shown in Figure 4, the size of community banks has been steadily increasing during the sample period, which indicates that these banks are consolidating perhaps to better meet lending needs in the local community.

To examine whether the new consolidated entity increases SB lending activity post-closure in the closed bank's county, we focus on the SB lending activity in the closed bank's main county– the county where the closed bank has the highest concentration of deposits as of *t-1*.[20] From our sample of community bank closures in which a new entity takes over, we form cohorts at the county-closure year consisting of the proforma consolidated entity (treated) and alternate controls groups of other banks with SB lending presence in the treatment county.[21] Specifically, in each cohort, the control group includes banks that did not engage in a consolidation before the closure year (*Not yet treated*) and/or those that did not engage in consolidations during our sample period (*Never Treated*). We construct a pro-forma consolidated entity by aggregating financial data from call reports for the closed bank and the new entity (acquirer) and aggregate SB lending activity at the closed bank-county-year level for the closed bank and the acquirer from *t-3* to *t-1* and obtain SBL originations data for the consolidated entity through $t{+}3$, focusing on the seven-year window (*t-3* to *t+3*) around each closure in the treatment county. For this analysis we require that the consolidated entity have county-level SBL originations data in both the pre- and post-closure period; thus, this analysis includes only CRA-reporting banks. We also drop deals in which the treatment counties experience another bank closure within the seven-year window (i.e., we include only non-overlapping deals in a county). Some counties experience several closures in the same year (i.e., some cohorts have multiple treated banks). We collect similar SB lending and financial data for the control group of banks.

We examine SB lending activity by the consolidated entity in the closed bank's main county employing the following the following stacked DiD regressions:

$$Ln\ (SB\ lending)_{icjt} = \alpha + \beta_1\ Post_{tj} \times Treat_i + \mathrm{Z}_{it} + \gamma_{icj} + \delta_{cjt}\ \varepsilon_{j,t} \tag{4}$$

where, $Ln(SB\ Lending)_{ijct}$ is the natural log of one plus the amount of SBL originations (*SBL originations to small firms*) for bank *i* in cohort *cj* (i.e., in county *c* and treatment year *j*) in year *t*. $Treat_i$ is an indicator that equals one for the proforma consolidated entity(ies) in cohort *cj* and zero otherwise; $Post_{tj}$ is an indicator variable equal to one starting the year after the bank closure in cohort *cj* and zero otherwise. Z_{it} is a

[20] In our sample of 5,620 community bank closures in which a new entity takes over, the closed bank's main county is the county of its headquarters in 91% of the deals. The mean (median) fraction of deposits held by closed banks in their main county is 82.3% (99.8%).
[21] In line with our county-level analysis, we form cohorts starting in 2002 to ensure we have three years in the pre-treatment period in each cohort.

vector of lagged bank-level controls that includes *Size*- log of book value of assets*; ROA*, net income-to-assets*; Loans-to-assets; Capital ratio,* equity-to-assets; *NPL ratio*, nonperforming loans-to-total loans, and *SBL-to-loans*, small business loans-to-total loans. *Treat* and *Post* are excluded from the estimation because they are subsumed by the fixed effects, which include bank-by-cohort fixed effects (γ_{icj}) to control for other confounding bank level factors, and cohort-by-year fixed effects (δ_{cjt}) that control for time-varying county level factors. [22] We double cluster standard errors at the bank and year level.

Results are shown in Table 9. In columns (1)-(2) the control group includes *Not yet* and *Never treated* banks. In columns (3)-(4), we show results using a matched sample in which we match each treated proforma bank to one of the control banks in the cohort that is closest in size and has similar fraction of SB loans outstanding in its portfolio as of *t-1*.

The results show that the consolidated entity increases SB lending post-closure in the treatment county relative to the control group. The coefficients on the interaction term *Post* x *Treat* are positive and significant across all model specifications. Taking the coefficient from column (1), results reveal a. 0.642 higher increase in *Ln(SBL originations)* by the consolidated entity post-closure relative to the control sample, which represents a 10.24% increase relative to its mean (6.27). Results are of similar magnitude for *Ln(SBL originations to small firms)* as well as when we use the matched control sample.

We also examine the parallel trends assumption underlying our stacked DiD analysis by replacing *Post* with timing indicator variables equal to one for years *t-3* through *t+3*. In line with the parallel-trends assumption, in un-tabulated results we find insignificant coefficients on the interaction terms between *Treat* and the pre-treatment indicator variables, with positive and significant coefficients on the interaction terms for the post-treatment indicator variables, which suggests that treatment and control banks follow similar patterns in terms of SBL originations in the pre-closure period.

In Panel B of Table 9, we examine whether the consolidated entity's SB lending activity differs based on bank size and county characteristics that were shown to affect the county-level results. For brevity, we

[22] Because our cohorts are formed at the county-bank closure year level, cohort-by-year fixed effects are in essence cohort-by county-year fixed effects that control for time-varying county factors.

report results using all control banks, noting that many of the interactions terms are subsumed by the fixed effects. In columns (1)-(4) we show results for *Ln(SBL originations)*, while columns (5)-(8) show results using *Ln(SBL originations to small firms)*.

Consistent with the county-level results, we find that the post-closure increase in SBL originations by the consolidated entity is smaller when the acquirer is a large bank. While results show no differential effects in distressed and underserved counties, the increase in SB lending is significantly larger in counties with a relatively large presence of other community banks. The latter results suggest that the observed increase in SB lending post-community bank closures is driven by community banks, both incumbent banks as well as by the consolidated entity.

6 The importance of the GFC on SB lending activity and Robustness at the county level.

During the sample period the world experienced the GFC, which had very important implications for all banks. Most of the impact was related to increased attention to bank risk taking and closer scrutiny by bank regulators. To examine the whether the GFC had an impact on SB lending we re-run our county-level analysis for the pre-GFC period (1999-2006) and the post-GFC period (2010-2020).

In Table 10 we show results from estimations of equation (3) for the pre- (post-) GFC period in the odd- (even-) numbered columns. For brevity, we include results using the baseline control group (*Not yet treated and never treated*). The results show an increase in SBL originations after the loss of a community bank in the post-GFC period, while the coefficient estimates are negative but insignificant on *Post* x *Treat* in the pre-GFC period.[23] The results suggest that the observed increase in SBL originations in counties that lose a community bank is a post-GFC phenomenon.

In additional analyses (not tabulated), we rerun the analysis of SBL originations by bank size aggregating SBL originations at the county-year level across community banks and large banks, separately for the pre- and post-GFC period. Results show that in the *pre-GFC* period the loss of a community bank in a county has no effect on subsequent SB lending by community banks. These results suggest that the observed

[23] This result related to the pre-GFC period is consistent with Jagtiani, Kotliar, and Maingi (2016) who examine the change in SBL-to-total assets from pre-merger to post-merger relative to peer non-merged banks.

increase in SB lending after community bank closures is driven by community banks in the post-GFC period. We also replicate results in Table 10 separately for the pre-GFC and post-GFC period for distressed and underserved counties. We do not find a differential effect for distressed or underserved counties in either period. For underserved counties, we find a negative and marginally significant (at the 10% level) coefficient on the triple interaction term, *Post* x *Treat* x *Underserved* in the *post-GFC* period for *Ln(Total SBL originations).*

While the reactions to the GFC were primarily focused on the risk-taking of large banks, the GFC also had important implications for community banks and their operations as well. Overall, the results suggest that the observed effect on SB lending in the *post-GFC* period is driven by SB lending activity by community banks. Interestingly, the results also show that the increase in SB lending by community banks after the closure is only significant in the *post-GFC* period. Though there are potential implications of the GFC for banking in general, there also were changes related to the growth of banking and data technology along with the expansion of Fintech firms in small business lending. We are unable to disentangle the direct effects of the GFC from these changes but simply use it as a reference point and not necessarily as causal effect.

6.2 Robustness tests.

We conduct a number of robustness tests and present results in the Internet Appendix. In our main analyses, we rely on the event-based stacked regressions approach, using cohorts of treatment counties (counties experiencing a community bank closure) and alternate control groups. To examine the robustness of our results, we replicate our main results but limit our control group to a propensity score (PSM)-matched sample of counties. For each treatment county, we find the closest match based on propensity scores obtained from logit regressions using the indicator *Treat* as a dependent variable. The logit regressions use the same controls used in our main analysis (Table 3). Regressions using the PSM-matched sample continue to show significant increase in SBL originations post-closures in treatment counties, relative to the PSM-matched control county. Using the PSM-matched sample we confirm the results are stronger in the post-GFC period and for community bank closures in counties with higher ex-ante community bank presence.

Because the CRA data are only available for a subset of banks that meet the reporting threshold, our results do not capture all SB lending at the county level around the closure of a community bank. One potential concern with this is that our results could be mechanical; when a non-CRA reporting bank closes and is taken over by a CRA-reporting entity, our data fails to capture SB lending by the closed bank prior to its closing but will pick up the SB lending activity by the consolidated entity after closure. We perform several tests that mitigate these concerns. First, to capture total SBL originations in a county, we include SBA 7A loan originations as a proxy for the SB lending of non-CRA reporting banks and find similar results. Second, our results show that there is an increase in lending around bank closures by "other banks"- CRA-reporting banks not involved with the bank closure or consolidation in the county. Because the lending by other banks excludes any lending by the closed bank and the consolidated entity, there is no reason to believe that such results could be mechanical. Finally, because our data captures loan originations, the entity taking over a non-CRA reporting bank would still have to originate new loans in the closed bank's county for our data to pick up an increase in SBL originations in the county; observing SBL originations in the closed bank's county by the consolidated entity would alleviate the main concerns about SB lending drying up after a community bank closes.

To further examine the robustness of our results, we estimate panel regressions of SB lending activity in the county using lagged indicators for the loss of a community bank in a county as key explanatory variable. The results confirm that the loss of a community bank is associated with significant increase in SBL originations in the county in the following year. The effect of community bank failures is weaker in these regressions and only significant for loans to small firms.

We also examine the effects associated with the magnitude of the loss of a community bank in a county. Specifically, we estimate stacked DiD regressions using only the treatment group of counties, including interactions between *Post* and *Deposit share-closed bank*- the share of deposits held by the closed bank in the county in the year before its closure. The interaction term *Post* x *Deposit share-closed bank* is positive and significant in regressions using *SBL originations to small firms*, suggesting that counties in which the closed bank had a larger share of deposits experience a more significant increase in *SBL originations to small firms* after the bank's closure. When assessing the effect on lending by other banks in the county, we observe positive and significant coefficients across all regression specifications. Thus, counties in which the closed bank held a larger fraction of deposits experience a more significant increase in SBL originations by competitor banks after the bank's closure.

Finally, we examine the impact of the loss of a community bank using an alternate definition of community banks: 1) Banks with assets <$2 billion. Results using this alternate definition of a community bank are similar to those presented in the paper.

7 Conclusion.

There has been a substantial reduction in the number of community banks since the turn of the century. This paper examines how the declining number of community banks affects local community economic development. We first show that small business lending positively impacts community economic development. Next, we explore how the closure of community banks affects this development through its impact on SBL originations in the affected areas.

The impact of community bank closures on community investment is nuanced. Interestingly, we find that in aggregate, community bank closures in a county are associated with a significant subsequent increase in SBL originations in those counties, relative to the control group. The effect is stronger in the post-GFC period though not likely driven by this event. We do not find differential effects in distressed or underserved counties but show that the increase in SBL originations post-closure is stronger in counties with a high share of deposits by community banks. The increase in SB lending is significantly smaller in counties in which consolidated bank is a large bank. In addition, we find stronger effects for SBL originations to small firms for deals in which the consolidated bank retains a presence (i.e., a full-service branch) in the affected county. The positive effects of community bank closures on subsequent SB lending activity in a county is partially driven by the increased SB lending activity of other local community banks.

In additional bank-level results, we find that the consolidated bank increases SB lending in the closed bank's county after closure, relative to the control group of banks. While we focus on community bank closures related to mergers/consolidations and to failures, we find similar effects across both types of closures. Importantly, we find that characteristics of the consolidating entities matter.

The aggregate finding of an increase in SBL originations in a county following community bank loss is driven primarily by changes in the structure of the SB lending market. We show that community banks have increased in size during the sample period. These large and likely more stable community banks focus more on larger SB loans and reduce their SB lending to small firms. Conversely, large banks have increased their SB lending to small firms and small SBL originations over the same period likely driven by the growth of lending technology. Moreover, the growth of Fintech firms has increased lending for smaller loans and loans to small firms as shown by prior literature.

The paper highlights the importance community banks for community economic development. We observe that only counties experiencing a large presence of community banks benefit when the county experiences a community bank closure. The evidence shows that when a local bank is lost, the characteristics of the new consolidated entity matter. We observe a positive impact on community development when the acquirer is a community bank, but the effect is less pronounced when the acquirer is a large bank. In general, the evidence supports the idea that community bank consolidations often lead to a larger and stronger entity following consolidation that increases community economic development. The evidence also supports an increase in this trend since 2010. Overall, the evidence supports the idea that a one size fits all response to the loss of a local community banks is not recommended to enhance community investment and county level characteristics and consolidated entity decisions should be key considerations in any policy response.

References

Angrist, J.D., and Pischke J.S., 2009, *Mostly Harmless Econometrics: An Empiricist's Companion* (Princeton University Press).

Baker, Andrew C., David F. Larcker, and Charles C. Y. Wang, 2022, How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics* 144, 370–395.

Barrios, John, 2021, Staggeringly Problematic: A Primer on Staggered DiD for Accounting Researchers, *SSRN Electronic Journal*.

Bartik, T. J., 1991. *Who benefits from state and local economic development policies?* W.E. Upjohn Institute for Employment Research.

Berger, A.N., Black, L. 2019. Small business lending: The roles of technology and regulation from pre-crisis to crisis to recovery. In A.N. Berger, P. Molyneux, and J. O. S. Wilson (eds). The Oxford Handbook of Banking, 3rd. ed. (Oxford: Oxford University Press), 431-469.

Berger, A. N., Black, L. 2011. Bank size, lending technologies, and small business finance. *Journal of Banking and Finance* 35, 724-735.

Berger, A. N., Bouwman, C. H. S., and Kim, D. 2017. Small bank comparative advantages in alleviating financial constraints and providing liquidity insurance over time. *Review of Financial Studies* 30, 3416-3454.

Berger, A. N., Goulding, W. and Rice, T. 2014. Do small businesses still prefer community banks? *Journal of Banking & Finance* 44, pp. 264–278.

Berger, A. N., Kashyap A.K., Scalise J.M., Gertler M., and Friedman B.M., 1995, The Transformation of the U.S. Banking Industry: What a Long, Strange Trip It's Been, *Brookings Papers on Economic Activity* 1995, 55–218.

Berger, A.N., Miller, N.H., Petersen, M.A., Rajan, R.G., Stein, J.C., 2005. Does function follow organizational form? Evidence from the lending practices of large and small banks. *Journal of Financial Economics* 76, 237–269.

Berger, A. N., and Udell, G. F. 1995. Relationship lending and lines of credit in small firm finance. *Journal of Business* 68 (3): 351–81.

Berger A.N., Udell, G. F. 2002. Small business credit availability and relationship lending: The importance of bank organizational structure. *Economic Journal* 112, 32-53.

Brown, J.D. and Earle, J.S. 2017. Finance and growth at the firm level: Evidence from SBA loans. *Journal of Finance* 72, 1039-1080.

Blanchard, O., and Katz, L. 1992. Regional evolutions. *Brookings Papers on Economic Activity* 23, 1-75.

Callaway, B., and Sant'Anna P., 2021, Difference-in-Differences with multiple time periods, *Journal of Econometrics* 225. Themed Issue: Treatment Effect 1, 200–230.

Cengiz, D., Dube, A., Lindner, A., and Zipperer, B., 2019, The Effect of Minimum Wages on Low-Wage Jobs*, *The Quarterly Journal of Economics* 134, 1405–1454

Cole, R.A., Goldberg, L. G., and White, L. J. 2004. Cookie cutter vs. character: The micro structure of small business lending by large and small banks. *Journal of Financial and Quantitative Analysis* 39, 227-251.

de Chaisemartin, C and D'Haultfoeuille, X, 2022, Two-way fixed effects and difference-in-differences with heterogeneous treatment effects: A survey, NBER Working Paper 29691.

DeYoung, R., Gron, A., Torna, G., and Winton, A., 2015, Risk Overhang and Loan Portfolio Decisions: Small Business Loan Supply before and during the Financial Crisis, *The Journal of Finance* 70, 2451–2488.

Ding, L., Lee, H., and Bostic W. 2018. Effects of the Community Reinvestment Act (CRA) on small business lending. Federal Reserve Bank of Philadelphia Working Paper. https://doi.org/10.21799/frbp.wp.2018.27.

Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. 2020. Bartik instruments: What, when, why, and how? *American Economic Review* 110, 2586-2624.

Goodman-Bacon, A., 2021, Difference-indifference with variation in treatment timing, *Journal of Econometrics* 225(2), 254-277.

Gopal, M. and P. Schnabl. 2022. The rise of finance companies and fintech lenders in small business lending. *Review of Financial Studies*, 35(11) 4859-4901.

Gormley, T. A. and Matsa D. A., 2011, Growing out of trouble? Corporate responses to liability risk, Review of Financial Studies 24(8), 2781-2821.

Jagtiani, J., Kotliar, I. and Maingi, R. Q. 2016. Community banking mergers and their impact on small business lending. *Journal of Financial Services Research* 27, 106-212.

Levine, R., Lin, C., Peng, Q, and Xie W. 2020, Communication within banking organizations and small business lending. *Review of Financial Studies* 33 (12), 5750-5783.

Levine, R, Lin, C., and Xie, W. 2020, Local financial structure and economic resilience, http://dx.doi.org/10.2139/ssrn.3755560

Nguyen, H-L. Q. 2019. Are credit markets still local? Evidence from branch closings. *American Economic Journal: Applied Economics* 11, 1-32.

Peek, J., and Rosengren E. S. 1998. Bank consolidation and small business lending: It's not just bank size that matters. *Journal of Banking and Finance* 22, 799-819.

Sanderson, E. and Windmeijer, F. 2016. A weak instrument F-test in linear IV models with multiple endogenous variables. *Journal of Econometrics* 190 (2), 212-221.

Stein, J. C., 2002. Information production and capital allocation: Decentralized versus hierarchical firms. *Journal of Finance* 57, 1891-1921.

Stock, J. H. and Yogo, M. 2005. Testing for weak instruments in linear IV regression. In D.W.K. Andrews and J.H. Stock, eds. *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*. Cambridge: Cambridge University Press, 2005, 80−108.

Strahan, P. E., and Weston, J. P. 1998. Small business lending and the changing structure of the banking industry. *Journal of Banking and Finance* 22, 821-845.

Table 1. Select descriptive statistics.

The table provides select descriptive statistics of the main county-level variables used in our analyses. Our final county-level panel dataset consists of 3,151 counties. Statistics are calculated at county-year level during the period from 1999 to 2019. All variables are defined in Appendix A.

Community Development	N	Mean	Median	Std. dev
Δ Ln (Small establishments)	51,574	0.001	0	0.032
Δ Ln (Employment)	51,581	0.005	0.006	0.029
Δ Ln (Small firm employment)	50,110	0.003	0.006	0.053
Community Investment				
Ln(SBL originations)	51,581	10.054	9.886	1.686
Ln (SBL originations to small firms)	51,581	9.249	9.156	1.693
Ln (Total SBL originations)	51,581	10.090	9.918	1.669
Controls				
Change in HPI %	51,581	0.026	0.025	0.056
Population growth	51,581	0.004	0.003	0.014
Ln (average wages)	51,581	10.41	10.402	0.239
Growth in per capita personal income	51,581	0.035	0.035	0.045
HFI deposits	51,581	0.272	0.232	0.156
Loans-to-assets	51,581	0.634	0.64	0.069
Capital ratio	51,581	0.105	0.104	0.015
NPL-to-loans	51,581	0.014	0.008	0.015
Share of deposits- top 4 banks	51,581	7.944	0	13.903
Distressed county	51,581	0.222	0	0.416
Underserved county	51,581	0.132	0	0.338
Key Variables				
Loss of community bank	51,581	0.184	0	0.387

Table 2. Community investment and economic development.

This table reports the results of 2SLS regressions estimating the determinants of community economic development during the period from 1999 to 2019. The dependent variables include the change in the natural logarithm of 1) *Small establishments;* 2) *Employment; and* 3) *Small firm employment*– the employment in the county by firms with fewer than 50 employees. Our key explanatory variable is the *ΔLn(SBL originations)* - the change in natural log of SBL originations at the county level. Columns (1) through (6) show results from 2SLS regressions in which we instrument *ΔLn(SBL originations)* with a Bartik-like instrumental variable (Bartik, 1991). Specifically, we use as an instrument for *ΔLn(SBL originations)* at the county level, the (predetermined) share of deposits in each county by community banks (<$10B in assets) and large (>$10B) banks times the aggregate *ΔLn(SBL originations)* for each type of bank at the national level. The first- (second-) stage results are shown in the even- (odd-) numbered columns. Controls include *Change in HPI (%); Population growth; Ln(wages)*, and *Growth in PCPI*. The last row reports the Sanderson-Windmeijer (2016) multivariate *F*-test of excluded instruments. Standard errors are clustered at the county and year level. *t*-statistics are reported in parentheses. All variables are defined in Appendix A. *** (**) {*} denotes significance at the 1% (5%) {10%} level.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	ΔLn(SBL originations)	ΔLn(Small establishments)	ΔLn(SBL originations)	ΔLn(employment)	ΔLn(SBL originations)	ΔLn(small firm employment)
	First-stage		First-stage		First-stage	
Instrumented *ΔLn(SBL originations)*		0.136***		0.078***		0.135**
		(4.20)		(3.07)		(2.43)
Bartik instrument	0.223***		0.223***		0.226***	
	(5.50)		(5.50)		(5.53)	
Change in HPI %(t-1)	0.216***	0.021**	0.216***	0.026***	0.215***	-0.014
	(5.39)	(2.03)	(5.39)	(3.29)	(5.26)	(-0.86)
Population growth(t-1)	-0.023	0.232***	-0.023	0.193***	-0.012	0.043
	(-0.14)	(6.77)	(-0.14)	(4.65)	(-0.07)	(1.29)
Ln(average wages)(t-1)	-0.126***	0.016***	-0.126***	-0.030***	-0.135***	-0.097***
	(-4.36)	(2.58)	(-4.36)	(-4.68)	(-4.54)	(-8.91)
Growth in per capita personal income(t-1)	-0.006	0.043***	-0.006	0.075***	-0.004	0.049***
	(-0.12)	(5.19)	(-0.12)	(10.86)	(-0.07)	(4.53)
Observations	51,032	51,032	51,039	51,039	49,570	49,570
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Sanderson-Windmeijer F-test	30.23		30.24		30.58	

Table 3. Loss of community banks and community investment.

This table presents results from event-based stacked DiD regressions estimating the effects of the loss of a community bank in a county on proxies for community investment during the period from 1999 to 2019. The treatment group consists of counties that experience the loss of a community bank. We form cohorts of treatment counties and use as controls counties that have not yet experienced a loss of a community bank (Not yet treated) and/or those that did not experience the loss of a community bank during our sample period (Never treated). We restrict the sample period to t-3, to t+3 around the "treatment" year in each cohort and form cohorts starting in 2002 to ensure we have three years in the pre-treatment period in each cohort. *Post* is an indicator equal to one starting the year after the loss of a community bank in county *c* in a treatment cohort and zero otherwise. Treat is an indicator equal to one for counties that lose a community bank and zero otherwise. Controls include: *HFI-deposits*; *Loans-to-assets*; *Capital ratio*; *Nonperforming loans-to-loans*; *Change in HPI (%)*; *Population growth*; *Ln(average wages)*, *Growth in per capita personal income*, and *Share of deposits-top 4 banks*. We rescale Herfindahl-deposits (dividing it by 1000) in the regressions. We show results using as control groups: Not yet treated and never treated, (columns (1)-(3)) and Never treated (columns (4)-(6)). Standard errors are clustered at the county-by-treatment cohort level. t-statistics are reported in parentheses. All regressions include county-by-cohort and year-by-cohort fixed effects. All variables are defined in Appendix A. *** (**) {*} denotes significance at the 1% (5%) {10%} level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(SBL originations)	Ln(SBL originations to small firms)	Ln (Total SBL originations)	Ln(SBL originations)	Ln(SBL originations to small firms)	Ln (Total SBL originations)
Control Group:	Not yet treated and never treated			Never treated		
Post x Treat	0.071**	0.084**	0.059**	0.072**	0.078*	0.062**
	(2.55)	(2.31)	(2.19)	(2.31)	(1.95)	(2.02)
HFI deposit t-1	0.575***	0.629***	0.662***	0.712***	1.068***	0.680***
	(3.76)	(3.26)	(4.39)	(3.03)	(4.19)	(2.92)
Loans-to-assets t-1	0.209**	0.296**	0.206**	0.020	0.487***	-0.026
	(2.02)	(2.19)	(1.99)	(0.15)	(2.61)	(-0.18)
Capital ratio t-1	-1.521***	-2.615***	-1.426***	-1.606***	-3.716***	-1.624***
	(-4.50)	(-6.07)	(-4.28)	(-2.90)	(-5.17)	(-2.98)
NPL-to-loans t-1	0.389	-0.046	0.557	-0.293	-0.105	0.046
	(0.85)	(-0.08)	(1.18)	(-0.54)	(-0.15)	(0.08)
% Change in HPI(t-1)	0.072	0.202***	0.102*	-0.084	0.185**	-0.054
	(1.35)	(2.71)	(1.86)	(-1.28)	(2.06)	(-0.80)
Population growth t-1	0.294	0.151	0.334	0.584	0.778	0.734
	(1.08)	(0.42)	(1.17)	(1.39)	(1.51)	(1.61)
Ln (average wages) t-1	0.036	-0.299**	0.067	-0.222	-0.449***	-0.192
	(0.30)	(-2.33)	(0.54)	(-1.34)	(-2.87)	(-1.11)
Growth in per capita personal income t-1	0.032	0.068	0.000	-0.081	-0.004	-0.177***
	(0.54)	(0.89)	(0.00)	(-1.21)	(-0.04)	(-2.68)
Share of deposits- top 4 banks t-1	-0.004	-0.006**	-0.004	0.001	-0.002	0.001
	(-1.56)	(-2.19)	(-1.58)	(0.66)	(-0.71)	(0.48)
Observations	20,378	20,378	20,378	11,125	11,125	11,125
Adjusted R^2	0.906	0.869	0.898	0.898	0.862	0.889
Year-by-cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County-by-cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 4. Probability of losing a community bank.

This table reports the results of OLS panel regressions at the county-year level estimating the probability that a county loses one or more community banks in a given year during the period from 1999 to 2019. Controls include: *HFI-deposits*; *Loans-to-assets*; *Capital ratio*; *Nonperforming loans-to-loans; Change in HPI (%); Population growth; Ln(wages), Growth in PCPI; Share of deposits- top 4; Small establishments %,* and *Loss of banks >$10B*. Standard errors are clustered at the county level. *t*-statistics are reported in parentheses. All variables are defined in Appendix A. *** (**) {*} denotes significance at the 1% (5%) {10%} level.

Dependent variable:	Pr. (Loss of a community bank)			
	(1)	(2)	(3)	(4)
Distressed county		-0.024***		
		(-5.19)		
Underserved county			0.018***	
			(3.17)	
High share of deposits - community				0.041***
				(7.78)
HFI deposit t-1	-0.378***	-0.368***	-0.386***	-0.400***
	(-19.90)	(-19.39)	(-20.11)	(-19.46)
Loans-to-assets t-1	-0.042	-0.050*	-0.047	-0.022
	(-1.39)	(-1.65)	(-1.58)	(-0.73)
Capital ratio t-1	-0.300**	-0.290**	-0.307**	-0.288**
	(-2.09)	(-2.04)	(-2.14)	(-1.99)
NPL-to-loans t-1	2.793***	2.875***	2.808***	3.003***
	(14.12)	(14.55)	(14.21)	(14.71)
% Change in HPI(t-1)	-0.002	-0.001	-0.006	-0.005
	(-0.05)	(-0.02)	(-0.17)	(-0.13)
Population growth t-1	1.620***	1.536***	1.665***	1.665***
	(7.34)	(7.08)	(7.40)	(7.38)
Ln (average wages) t-1	0.285***	0.273***	0.286***	0.287***
	(14.93)	(14.11)	(14.97)	(15.10)
Growth in per capita personal income t-1	0.016	0.006	0.015	0.017
	(0.43)	(0.17)	(0.42)	(0.46)
Share of deposits- top 4 banks t-1	0.001***	0.001***	0.001***	0.002***
	(5.62)	(5.77)	(5.61)	(7.19)
Small establishments % total t-1	-1.203***	-1.279***	-1.300***	-1.316***
	(-7.06)	(-7.47)	(-7.40)	(-7.70)
Loss -banks >$10B	-0.261***	-0.261***	-0.261***	-0.261***
	(-51.31)	(-51.30)	(-51.36)	(-51.18)
Observations	51,575	51,575	51,575	51,018
Adjusted R^2	0.127	0.128	0.127	0.128
Year fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes

Table 5. The loss of community banks and community investment, by county characteristics.

This table presents results from event-based stacked DiD regressions estimating the effects of the loss of a community bank in a county on community investment using three proxies for community investment - Ln(*SBL originations), Ln(SBL originations to small firms)* and *Ln(Total SBL originations)* – during the period from 1999 to 2019. The treatment group consists of counties that experience the loss of a community bank. We form cohorts of treatment counties and use as controls counties that have not yet experienced a loss of a community bank and those that did not experience the loss of a community bank during our sample period (*Not yet treated* and *Never treated*). We restrict the sample period to t-3, to t+3 around the "treatment" year in each cohort and form cohorts starting in 2002 to ensure we have three years in the pre-treatment period in each cohort. *Post* is an indicator equal to one starting the year after the loss of a community bank in county *c* in a treatment cohort and zero otherwise. *Treat* is an indicator equal to one for counties that lose a community bank and zero otherwise. Controls (unreported to conserve space) include: *HFI-deposits*; *Loans-to-assets*; *Capital ratio*; *Nonperforming loans-to-loans*; *Change in HPI (%)*; *Population growth*; *Ln(average wages)*, *Growth in per capita personal income*, and *Share of deposits- top 4 banks*. In Panel A we show results using interactions with two county type indicators: 1) *Distressed county* and 2) *Underserved county*. In columns (1)-(3) we show results using *Distressed county* indicator and columns (4)-(6) show results using interactions with *Underserved county*. Standard errors are clustered at the county-by-treatment cohort level. In Panel B we show results using interactions with *High deposit share-community banks*. *t*-statistics are reported in parentheses. All regressions include county-by-cohort and year-by-cohort fixed effects. All variables are defined in Appendix A. *** (**) {*} denotes significance at the 1% (5%) {10%} level.

Panel A. Impact in Distressed and Underserved Counties.						
	(1)	(2)	(3)	(4)	(5)	(6)
	Ln (SBL originations)	Ln (SBL originations to small firms)	Ln (Total SBL originations)	Ln(SBL originations)	Ln (SBL originations to small firms)	Ln (Total SBL originations)
Control Group	*Not yet treated and never treated*					
County type:	*Distressed*			*Underserved*		
Post x Treat x County Type	0.041	0.036	0.016	0.044	0.114	0.024
	(0.68)	(0.48)	(0.27)	(0.66)	(1.27)	(0.37)
Post x Treat	0.054*	0.063	0.052*	0.053*	0.055	0.052*
	(1.73)	(1.48)	(1.69)	(1.79)	(1.40)	(1.74)
Post x County Type	-0.037**	-0.053***	-0.028*	-0.020	0.019	-0.031*
	(-2.33)	(-2.63)	(-1.74)	(-1.10)	(0.83)	(-1.74)
Treat x County Type	-0.009	0.075	-0.023	-0.420**	-0.101	-0.064
	(-0.17)	(1.13)	(-0.45)	(-2.28)	(-0.42)	(-0.30)
County Type	-0.019	-0.079***	0.002	-0.006	-0.019	-0.004
	(-1.24)	(-3.86)	(0.15)	(-0.09)	(-0.27)	(-0.06)
Observations	20,378	20,378	20,378	20,378	20,378	20,378
Adjusted R^2	0.906	0.870	0.898	0.906	0.869	0.898
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County-by-cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 5. Loss of community banks and community investment, by county characteristics. Continued

Panel B. By deposit shares of community banks county type			
	(1)	(2)	(3)
	Ln (SBL originations)	Ln (SBL originations to small firms)	Ln (Total SBL originations)
Control group:		*Not yet treated and never treated*	
County type:		*High share of deposits of community banks*	
Post x Treat x County type	0.205***	0.269***	0.194***
	(3.78)	(3.89)	(3.59)
Post x Treat	-0.027	-0.054	-0.037
	(-0.84)	(-1.34)	(-1.10)
Post High deposit share-community banks	-0.005	-0.020	-0.002
	(-0.28)	(-0.86)	(-0.12)
Treat x High deposit share-community banks	-0.154***	-0.172**	-0.128**
	(-2.80)	(-2.34)	(-2.39)
High deposit share- community banks	-0.019	0.039	-0.036
	(-0.79)	(1.30)	(-1.55)
Observations	20,106	20,106	20,106
Adjusted R^2	0.907	0.870	0.899
Controls	Yes	Yes	Yes
Year-by-cohort fixed effects	Yes	Yes	Yes
County-by-cohort fixed effects	Yes	Yes	Yes

Table 6. Loss of community banks and community investment by new consolidated entity type.

This table presents results from event-based stacked DiD regressions estimating the effects of the loss of a community bank in a county on community investment using three proxies for community investment - Ln(*SBL originations)*, *Ln(SBL originations to small firms)* and *Ln(Total SBL originations)* – during the period from 1999 to 2019. The treatment group consists of counties that experience the loss of a community bank. We form cohorts of treatment counties and use as controls counties that have not yet experienced a loss of a community bank and those that did not experience the loss of a community bank during our sample period (*Not yet treated* and *Never treated*). We restrict the sample period to t-3, to t+3 around the "treatment" year in each cohort and form cohorts starting in 2002 to ensure we have three years in the pre-treatment period in each cohort. *Post* is an indicator equal to one starting the year after the loss of a community bank in county c in a treatment cohort and zero otherwise. *Treat* is an indicator equal to one for counties that lose a community bank and zero otherwise. Controls (unreported to conserve space) include: *HFI-deposits*; *Loans-to-assets*; *Capital ratio*; *Nonperforming loans-to-loans*; *Change in HPI (%)*; *Population growth*; *Ln(average wages)*, *Growth in per capita personal income*, and *Share of deposits- top 4 banks*. In Panel A we show results using interactions with *Large* – an indicator equal to one for treatment counties in which the new entity (acquirer) taking over the closed bank is a large bank (>$10B). In Panel B we show results using interactions with *Presence post-closure* – an indicator equal to one for treatment counties in which the new entity (acquirer) continues to have a presence (a full-service branch) in the county after the small bank's closure. Standard errors are clustered at the county-by-cohort level. *t*-statistics are reported in parentheses. All regressions include county-by-cohort and year-by-cohort fixed effects. All variables are defined in Appendix A. *** (**) {*} denotes significance at the 1% (5%) {10%} level.

Panel A. Impact of New Entity's Size.

	(1)	(2)	(3)
	Ln (SBL origination)	Ln (SBL originations to small firms)	Ln (Total SBL originations)
Control Group:		*Not yet treated and never treated*	
Post x Treat x Large	-0.162***	-0.187***	-0.133**
	(-2.96)	(-2.65)	(-2.50)
Post x Treat	0.111***	0.131***	0.093***
	(3.45)	(3.01)	(2.92)
Observations	20,378	20,378	20,378
Adjusted R^2	0.906	0.869	0.898
Controls	Yes	Yes	Yes
Year-by-cohort fixed effects	Yes	Yes	Yes
County-by-cohort fixed effects	Yes	Yes	Yes

Panel B. Impact of New Entity's Post Closure Presence

	(1)	(2)	(3)
	Ln (SBL originations)	Ln (SBL originations to small firms)	Ln (Total SBL originations)
Control Group:		*Not yet treated and never treated*	
Post x Treat x Presence-post closure	0.070	0.174**	0.051
	(1.23)	(2.41)	(0.91)
Post x Treat	0.050	0.034	0.045
	(1.56)	(0.78)	(1.43)
Observations	20,378	20,378	20,378
Adjusted R^2	0.906	0.869	0.898
Controls	Yes	Yes	Yes
Year-by-cohort fixed effects	Yes	Yes	Yes
County-by-cohort fixed effects	Yes	Yes	Yes

Table 7. Loss of community banks and community investment by other banks in the county.

This table presents results from event-based stacked DiD regressions estimating the effects of the loss of a community bank in a county on three proxies for community investment by other banks in the county during the period from 1999 to 2019. Community investment proxies for other banks in the county are calculated by *excluding* lending by the closed bank and the new entity absorbing the closed bank. The treatment group consists of counties that experience the loss of a community bank. We form cohorts of treatment counties and use as controls counties that have not yet experienced a loss of a community bank (*Not yet treated*) and those that did not experience the loss of a community bank during our sample period (*Never Treated*). We restrict the sample period to t-3, to t+3 around the "treatment" year in each cohort and form cohorts starting in 2002 to ensure we have three years in the pre-treatment period in each cohort. *Post* is an indicator equal to one starting the year after the loss of a community bank in county *c* in a treatment cohort and zero otherwise. *Treat* is an indicator equal to one for counties that lose a community bank and zero otherwise. Controls (unreported to conserve space) include: *HFI-deposits*; *Loans-to-assets*; *Capital ratio*; *Nonperforming loans-to-loans*; *Change in HPI (%)*; *Population growth*; *Ln(average wages)*, *Growth in per capita personal income,* and *Share of deposits- top 4 banks*. Panel A shows baseline results. In Panel B we show results using interactions with *High deposit share-community banks*. *t*-statistics are reported in parentheses. Standard errors are clustered at the county-by-cohort level. All regressions include county-by-cohort and year-by-cohort fixed effects. All variables are defined in Appendix A. *** (**) {*} denotes significance at the 1% (5%) {10%} level.

Panel A. Lending by other banks in the county.			
	(1)	(2)	(3)
	Ln (SBL originations) other banks	Ln (SBL originations to small firms) other banks	Ln (Total SBL originations) other banks
Post x Treat	0.092***	0.111***	0.080***
	(3.29)	(3.01)	(2.95)
Observations	20,378	20,378	20,378
Adjusted R^2	0.906	0.869	0.897
Controls	Yes	Yes	Yes
Year-by-cohort fixed effects	Yes	Yes	Yes
County-by-cohort fixed effects	Yes	Yes	Yes

Panel B. Lending by other banks in the county, by share of deposits of community banks county type.			
	(1)	(2)	(3)
	Ln (SBL originations) other banks	Ln (SBL originations to small firms) other banks	Ln (Total SBL originations) other banks
Post x Treat x High deposit share-community banks	0.200***	0.268***	0.189***
	(3.68)	(3.87)	(3.49)
Post x Treat	-0.005	-0.029	-0.015
	(-0.16)	(-0.71)	(-0.45)
Post High deposit share-community banks	-0.005	-0.019	-0.002
	(-0.26)	(-0.85)	(-0.10)
Treat x High deposit share-community banks	-0.147***	-0.166**	-0.122**
	(-2.63)	(-2.21)	(-2.24)
High deposit share- community banks	-0.020	0.037	-0.038
	(-0.86)	(1.24)	(-1.62)
Observations	20,106	20,106	20,106
Adjusted R^2	0.906	0.869	0.898
Controls	Yes	Yes	Yes
Year-by-cohort fixed effects	Yes	Yes	Yes
County-by-cohort fixed effects	Yes	Yes	Yes

Table 8. Loss of community banks and community investment by community banks and large banks for small firms and all other firms.

This table presents results from event-based stacked DiD regressions estimating the effects of the loss of a community bank in a county on SB lending by community banks and large banks to small firms and all other firms. *SBL originations to other firms* is the difference between *SBL originations* and *SBL originations* to small firms during 1999 to 2019. We aggregate these measures at the county-year level across *Community banks and Large banks.* We form cohorts of treatment counties and use as controls counties that have not yet experienced a loss of a community bank and those that did not experience the loss of a community bank during our sample period (Not yet treated and Never Treated). We restrict the sample period to t-3, to t+3 around the "treatment" year in each cohort and form cohorts starting in 2002 to ensure we have three years in the pre-treatment period in each cohort. *Post* is an indicator equal to one starting the year after the loss of a community bank in county *c* in a treatment cohort and zero otherwise. Treat is an indicator equal to one for counties that lose a community bank and zero otherwise. Controls (unreported to conserve space) include: *HFI-deposits*; *Loans-to-assets*; *Capital ratio*; *Nonperforming loans-to-loans*; *Change in HPI (%)*; *Population growth*; *Ln(average wages)*, *Growth in per capita personal income*, and *Share of deposits- top 4 banks*. We rescale Herfindahl-deposits (dividing it by 1000) in the regressions. We show results using *Not yet treated* and *Never treated*. In columns (1)-(3)) we show results for lending by community banks and columns (4)-(6) show results for lending by large banks. Standard errors are clustered at the county-by-treatment cohort level. t-statistics are reported in parentheses. All regressions include county-by-cohort and year-by-cohort fixed effects. All variables are defined in Appendix A. *** (**) {*} denotes significance at the 1% (5%) {10%} level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(SBL originations)	Ln(SBL originations to small firms	Ln(SBL originations to other firms)	Ln(SBL originations)	Ln(SBL originations to small firms)	Ln(SBL originations to other firms)
Lending by:		Community banks			Large banks	
Control Group"				Not yet treated and never treated		
Post x Treat	0.153**	0.136	0.196**	0.114***	0.188***	0.072
	(2.04)	(1.54)	(1.97)	(2.68)	(3.20)	(1.13)
HFI deposit t-1	2.269***	1.819***	2.549***	0.035	-0.156	0.059
	(6.60)	(4.32)	(5.01)	(0.17)	(-0.56)	(0.19)
Loans-to-assets t-1	0.552*	0.807**	0.635	0.012	0.061	-0.331
	(1.90)	(2.34)	(1.51)	(0.07)	(0.26)	(-1.12)
Capital ratio t-1	-0.447	1.476	-2.647**	-1.785***	-3.796***	1.930**
	(-0.49)	(1.38)	(-1.97)	(-3.30)	(-5.14)	(2.34)
NPL-to-loans t-1	0.665	0.920	-2.829	1.340*	0.837	2.157*
	(0.55)	(0.61)	(-1.38)	(1.77)	(0.76)	(1.73)
% Change in HPI(t-1)	0.185	0.071	-0.614**	0.084	0.143	0.074
	(1.12)	(0.35)	(-2.48)	(1.03)	(1.35)	(0.50)
Population growth t-1	-2.346***	-2.820***	-1.410	0.361	0.056	0.445
	(-2.72)	(-2.92)	(-1.17)	(0.90)	(0.10)	(0.62)
Ln (average wages) t-1	0.102	0.473	-0.249	0.044	-0.460**	0.396
	(0.40)	(1.49)	(-0.68)	(0.22)	(-2.01)	(1.12)
Growth in per capita personal income	-0.652***	-0.349*	-0.173	-0.015	0.130	-0.214
	(-3.26)	(-1.77)	(-0.74)	(-0.18)	(1.20)	(-1.59)
Share of deposits- top 4 banks t-1	-0.016**	-0.017***	-0.023***	0.008***	0.011***	0.008***
	(-2.54)	(-2.82)	(-3.56)	(3.15)	(4.07)	(2.73)
Observations	20,378	20,378	20,378	20,378	20,378	20,378
Adjusted R^2	0.754	0.728	0.660	0.833	0.768	0.715
Year-by-cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County-by-cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 9. Bank-level results: Community investment around bank closures.

This table presents results from bank-level event-based stacked DiD regressions estimating community investment by banks around the closure of a community bank in a county during the period from 1999 to 2019. We form cohorts of treated and control banks at the county-bank closure year. We restrict the sample period to the seven years [-3,+3] around the community bank closure in the closed bank's main county (where the closed bank has the largest presence (share of deposits) as of *t-1*) and form cohorts starting in 2002 to ensure we have three years in the pre-treatment period in each cohort. The control group includes *Not yet treated* banks in the county that did not engage in a consolidation before the treatment year, and banks that did not engage in a consolidation during our sample period (*Never treated*). *Treat* is an indicator equal to one for the proforma consolidated entity (the new entity taking over the closed bank) and zero for the control banks (other banks in the county). *Post* is an indicator variable equal to one starting the year after the bank closure in each cohort and zero otherwise. Bank-level controls include *Size*; *ROA*; *Loans-to-assets*; *Capital ratio*; *NPL ratio*, and *SBL-to-loans*. All regressions include bank-by-cohort fixed effects, and we control for time-varying county level factors by including cohort-by-year fixed effects. In columns (3)-(4) we show results from a matched sample, where we match each treatment bank to a control bank in its cohort that is closest in size and proportion of SB loans outstanding in its loan portfolio. In Panel B, we show results using as controls all other banks in the county including interactions with the following indicator variables: 1) *Large*, which equals one for if the new entity (acquirer) taking over the closed bank is a large bank; 2) *Distressed county;* 3) *Underserved county*; and 4) *High deposit share-community banks*. All regressions include bank-by-cohort fixed effects and cohort-by-year fixed effects. We cluster standard errors at the bank and year level. Robust *t*-statistics are reported in parentheses. *** (**) {*} denotes significance at the 1% (5%) {10%} level.

Panel A. Post-Closure SB lending by banks in treatment county.				
Dependent variable:	Ln(SBL originations)	Ln(SBL originations to small firms)	Ln(SBL originations)	Ln(SBL originations to small firms)
	(1)	(2)	(3)	(4)
Control group:	*Not yet and never treated*		*1:1 Matched sample*	
Post x Treat	0.642***	0.452**	0.656***	0.501***
	(9.84)	(2.58)	(10.05)	(4.07)
Size	0.121	0.421*	0.037	0.047
	(0.71)	(1.96)	(0.27)	(0.22)
ROA	0.090	0.239	0.034	0.169**
	(1.54)	(1.50)	(1.12)	(2.73)
Capital ratio	-0.041**	0.018	-0.040***	-0.027
	(-2.33)	(0.41)	(-3.17)	(-0.81)
NPL ratio	7.846	3.271	4.274	5.489
	(1.51)	(0.49)	(1.21)	(1.20)
Loans-to-assets	0.005	0.026**	0.014***	0.036***
	(1.32)	(2.17)	(3.48)	(3.86)
SBL-to-loans	0.478	1.897	1.021*	1.841
	(0.75)	(1.26)	(1.84)	(1.31)
Bank x cohort fixed effects	Yes	Yes	Yes	Yes
Cohort x year fixed effects	Yes	Yes	Yes	Yes
Observations	33,930	33,930	8,911	8,911
Adjusted R^2	0.825	0.740	0.850	0.773

Table 9. Bank-level results: Community investment around bank closures. Continued.

Panel B. Impact of bank size and county characteristics.								
	(1)	(2)	(3)	(4)	(5)	(6)		
Dependent variable:	Ln(SBL originations)				Ln(SBL originations to small firms)			
Control Group	*Not yet and never treated*							
Post x Treat	0.735***	0.621***	0.633***	0.598***	0.556**	0.411*	0.444**	0.402*
	(6.38)	(5.96)	(5.68)	(5.39)	(2.57)	(1.99)	(2.17)	(1.98)
Post x Treat x Large bank acquirer	-0.488***				-0.543**			
	(-3.44)				(-2.49)			
Post x Treat x Distressed county		0.144				0.283		
		(0.68)				(0.85)		
Treat x Distressed county		-0.274				-0.421		
		(-1.46)				(-1.32)		
Post x Treat x Underserved county			0.222				0.197	
			(0.69)				(0.41)	
Treat x Underserved county			1.113***				1.562***	
			(3.16)				(4.13)	
Post x Treat x High share of small bank deposits				0.432**				0.696**
				(2.42)				(2.60)
Treat x High share of small bank deposits				-0.274				-1.617**
				(-1.47)				(-2.76)
Observations	33,930	33,930	33,930	33,930	33,930	33,930	33,930	33,930
Adjusted R^2	0.825	0.825	0.825	0.825	0.740	0.740	0.740	0.740
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank x cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort x year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 10. Loss of community banks and community investment, pre- and post-GFC

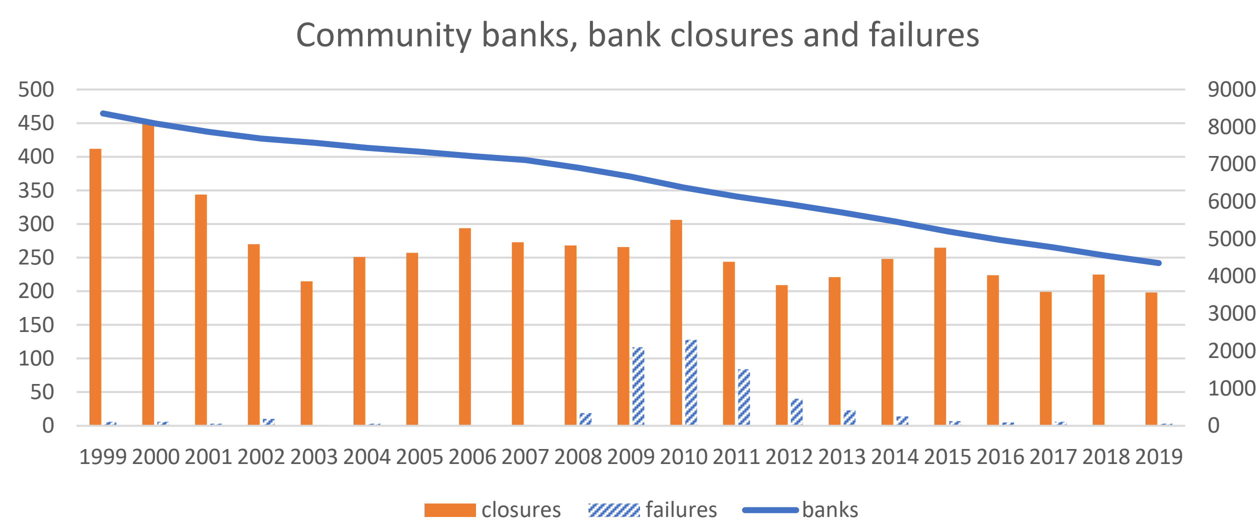
This table presents results from event-based stacked DiD regressions estimating the effects of the loss of a community bank in a county on community investment for the pre-GFC (1999-2006) and post-GFC (2010-12019) periods. The treatment group consists of counties that experience the loss of a community bank. We form cohorts of treatment counties and use as controls counties that have not yet experienced a loss of a community bank or those that did not experience the loss of a community bank during our sample period (Not year and never treated and Never Treated). We restrict the sample period to t-3, to t+3 around the "treatment" year in each cohort and form cohorts starting in 2002 to ensure we have three years in the pre-treatment period in each cohort. *Post* is an indicator equal to one starting the year after the loss of a community bank in county *c* in a treatment cohort and zero otherwise. Treat is an indicator equal to one for counties that lose a community bank and zero otherwise. Controls (unreported to conserve space) include: *HFI-deposits*; *Loans-to-assets*; *Capital ratio*; *Nonperforming loans-to-loans*; *Change in HPI (%)*; *Population growth*; *Ln(average wages)*, *Growth in per capita personal income,* and *Share of deposits- top 4 banks*. We rescale Herfindahl-deposits (dividing it by 1000) in the regressions. We show results using as control groups: Not yet treated and Never treated, (columns(1)-(3)) and Not yet treated (columns(4)-(6)). Standard errors are clustered at the county-by-treatment cohort level. t-statistics are reported in parentheses. All regressions include county-by-cohort and year-by-cohort fixed effects. All variables are defined in Appendix A. *** (**) {*} denotes significance at the 1% (5%) {10%} level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln (SBL originations)		Ln (SBL originations to small firms)		Ln(Total SBL originations)	
Treatment Group	Not yet and never treated				Never treated	
	Pre- GFC	*Post GFC*	*Pre-GFC*	*Post GFC*	*Pre-GFC*	*Post GFC*
Post x Treat	-0.037	0.129**	-0.056	0.214***	-0.026	0.090
	(-1.08)	(2.30)	(-1.31)	(2.79)	(-0.77)	(1.58)
HFI deposit t-1	0.958***	0.084	0.691**	0.493	1.024***	0.006
	(3.91)	(0.35)	(2.02)	(1.29)	(4.24)	(0.02)
Loans-to-assets t-1	-0.480***	-0.126	-0.720***	0.200	-0.422***	-0.217
	(-2.87)	(-0.66)	(-3.59)	(0.77)	(-2.58)	(-1.10)
Capital ratio t-1	-1.946***	1.106	-2.184***	-1.712	-1.920***	0.675
	(-3.62)	(1.10)	(-2.98)	(-1.31)	(-3.64)	(0.68)
NPL-to-loans t-1	-1.171	2.154***	-4.554**	2.395***	-0.778	2.540***
	(-0.77)	(3.34)	(-2.51)	(2.59)	(-0.50)	(3.90)
% Change in HPI(t-1)	0.949***	0.044	1.394***	0.205	0.853***	0.076
	(10.48)	(0.49)	(11.99)	(1.64)	(8.96)	(0.84)
Population growth t-1	-0.852*	-0.020	-1.558**	0.400	-1.464***	0.448
	(-1.86)	(-0.04)	(-2.56)	(0.65)	(-2.96)	(0.78)
Ln (average wages) t-1	-0.465**	0.003	-0.330	-0.493**	-0.347*	0.114
	(-2.30)	(0.02)	(-1.47)	(-2.32)	(-1.68)	(0.58)
Growth in per capita personal income t-1	-0.169*	0.194**	-0.222**	0.086	-0.202*	0.192**
	(-1.65)	(2.16)	(-2.07)	(0.71)	(-1.89)	(2.19)
Share of deposits- top 4 banks t-1	0.002	-0.090**	0.002	-0.083*	0.001	-0.090**
	(0.99)	(-2.20)	(1.05)	(-1.71)	(0.65)	(-2.14)
Observations	7,981	7,613	7,981	7,613	7,981	7,613
Adjusted R^2	0.920	0.876	0.891	0.815	0.918	0.863
Year-by-cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County-by-cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Figure 1. Community bank closures.

Panel A shows the number of community banks as of the fourth quarter of each year (right axis) and the total number of community bank closures and failures (left axis). Community banks are defined as commercial banks (FDIC entity type 10) with assets <$10 billion (in constant 2019 US $s.). Community bank closures include bank failures and mergers/consolidations. Bank failures are those with transaction code (CODE2XX) of 211 (Absorption- assisted) and 215 (Partial purchase or assumption – assisted), as well as failed banks where there was no acquirer involved, based on the FDIC's Failed Banks list. Merger/consolidations are those with transaction code of 221 (Absorption), 222 (Consolidated), or 223 (Merger). Data on closures and number of community banks were obtained from the FDIC's RIS merger and financial time series (FTS) databases, respectively. Panel B shows total SBL originations (community banks and other banks) and SBL originations by community banks. Data on SB loans are obtained from the CRA Disclosure files.

Panel A.



Panel B.

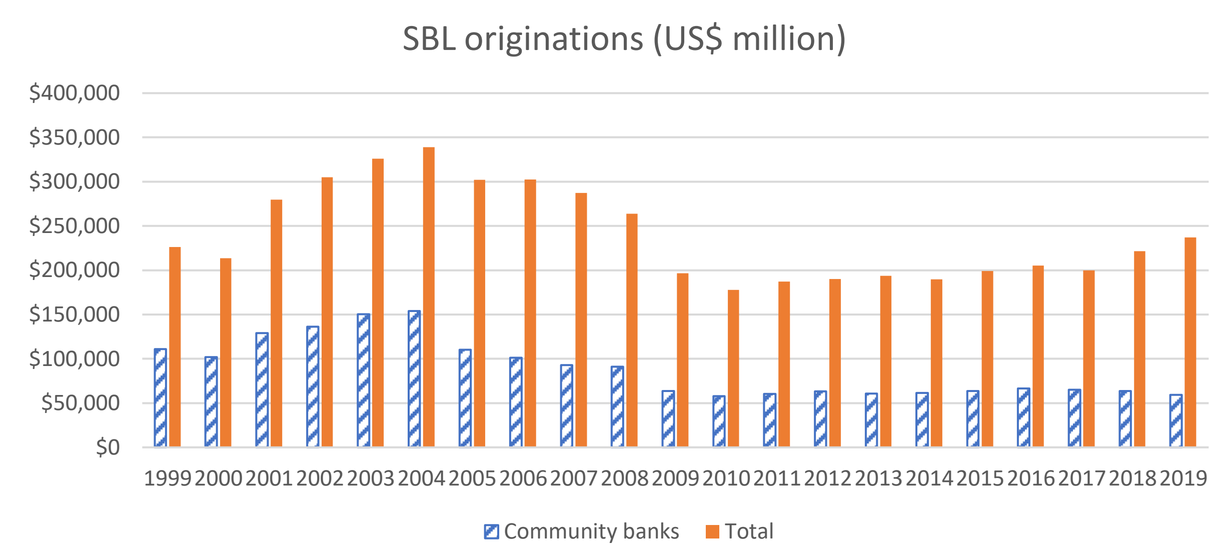


Figure 2. Community bank closures by county.

The figure shows the distribution of the number of community bank closures by county form 1999-2019. Community bank closures capture cases involving failure as well as mergers/consolidations of commercial banks with assets <$10B (in constant 2019 US $s). Data are obtained from the FDIC's RIS merger database, the FDIC's Bank Failures List, and the SOD database. A county is classified as losing a small bank due to closures if a bank with operations in the county closes during the year.

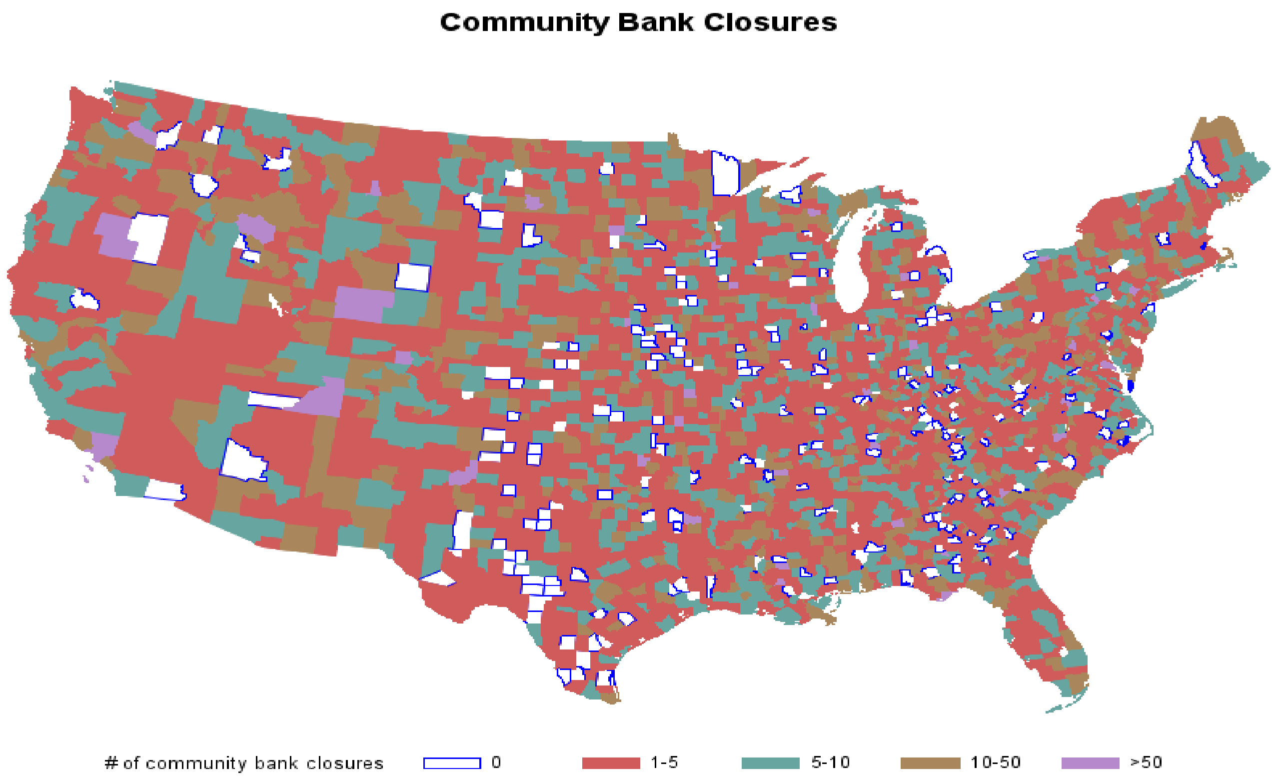


Figure 3. Diagnostic test of the parallel trends assumption.

This figure plots the coefficients on the interaction terms between the timing indicators (t-3, …, t+3) and indicators for our treatment counties (*Treat*) that lose a community bank. The dependent variable is Ln (SB loans), the natural log of one plus SB loan originations (constant 2019 US$000s) in the county. We form cohorts of treatment counties and use as controls counties that did not experience the loss of a small bank during our sample period (*Never Treated*). We restrict the sample period to t-3, to t+3 around the "treatment" year in each cohort and form cohorts starting in 2002 to ensure we have three years in the pre-treatment period in each cohort. Controls are the same ones used in Table 5. The solid dots represent the point estimates, and the lines represent the 95% confidence intervals. *Year 0* is chosen as the benchmark period. Standard errors are clustered at the county-by-treatment cohort level. All regressions include county-by-cohort and year-by-cohort fixed effects. All variables are defined in Appendix A.

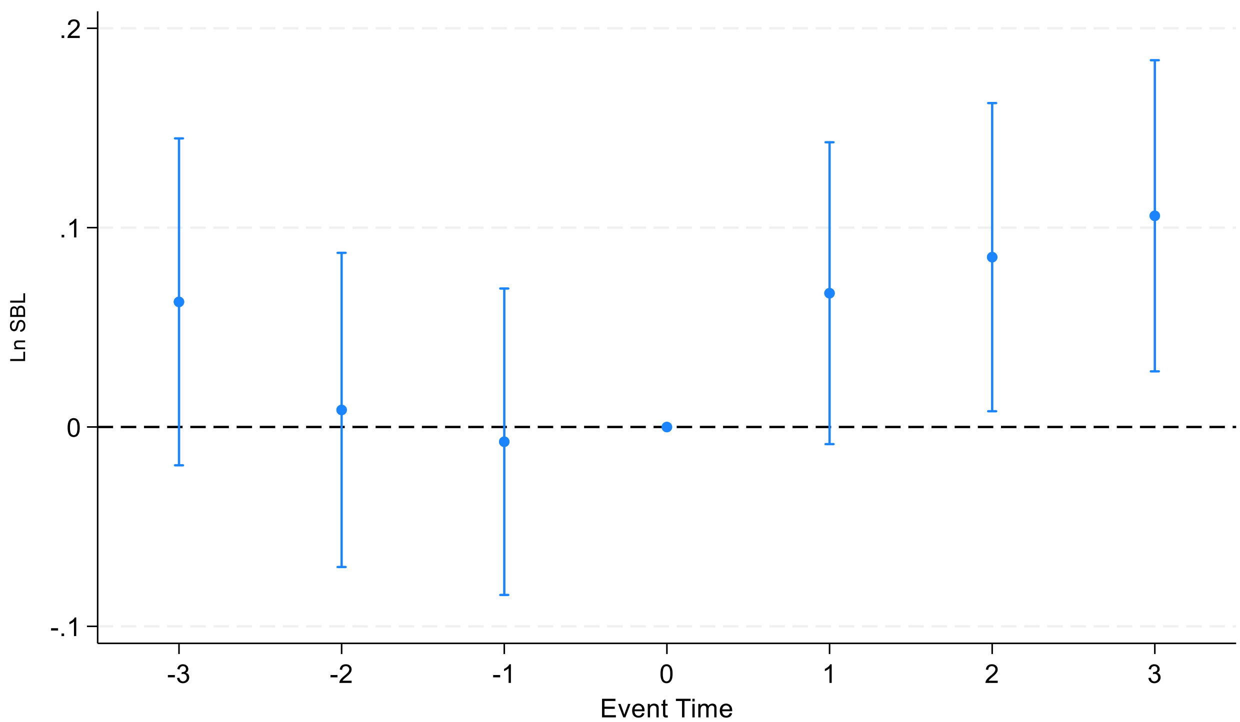
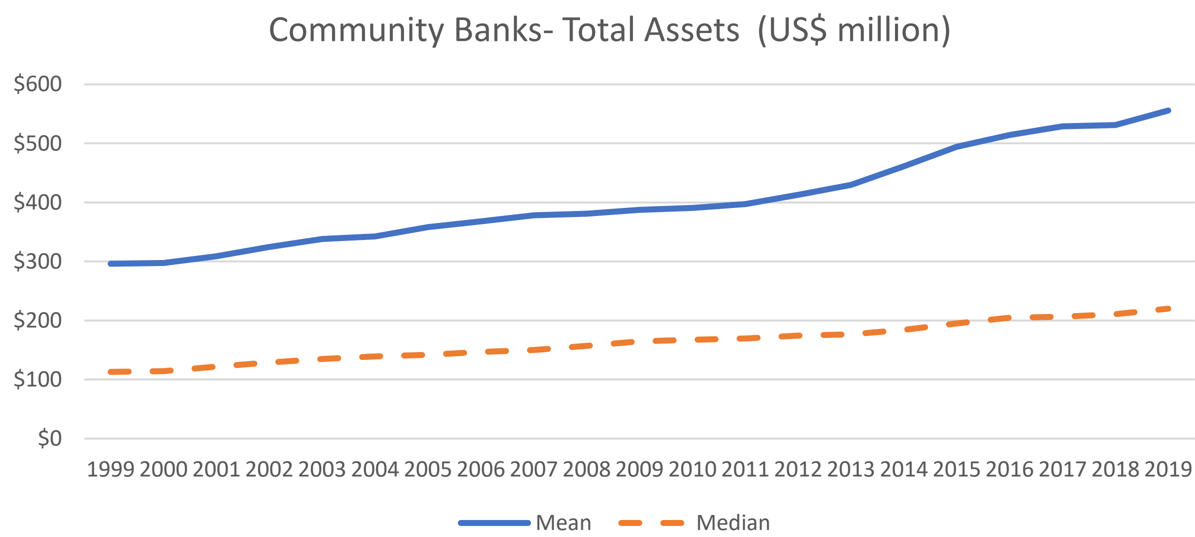


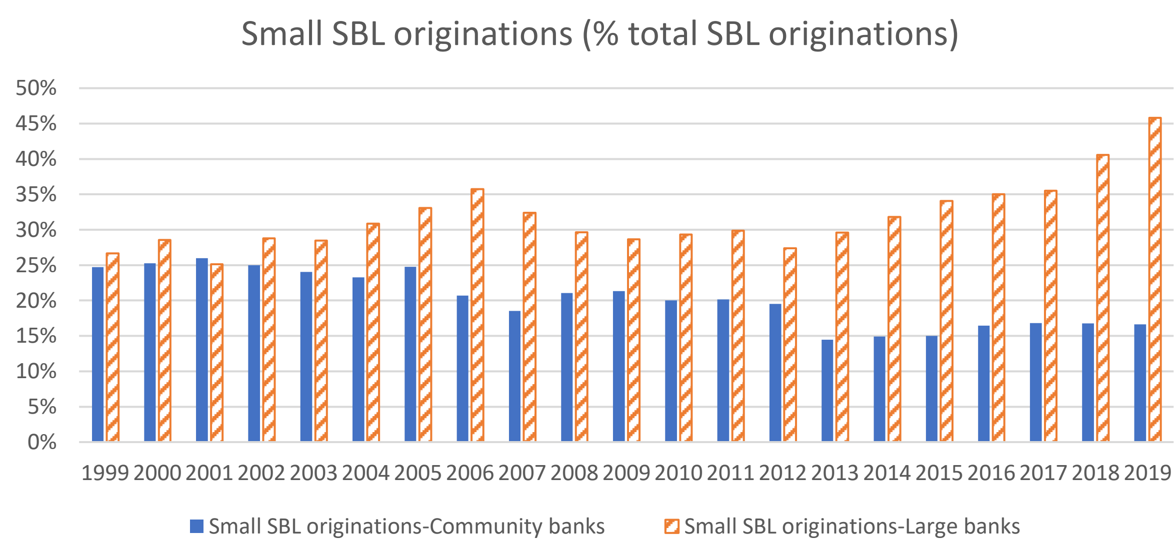
Figure 4. Community bank size and SB lending activity.

Panel A shows the distribution of the size of community banks (in constant 2019 US$ million) from 1999-2019. Community banks are commercial banks (FDIC's entity type #10) with assets <$10B (in constant 2019 US $s). Data are obtained from call reports through the FDIC's RIS database. In Panel B, we show the fraction of total SBL originations by loan size for Community banks and Large banks. The fraction of small SBL originations by community (*Large*) banks is the ratio of the aggregate small SBL originations by community (Large) banks-to-the aggregate SBL originations by community (Large) banks. Small SBL originations represent loans < $100K. Data on SBL originations are obtained from the CRA Disclosure files.

Panel A. Community Banks- Size by Year



Panel B. SB Loan Originations by Loan size



Appendix A. Variable definitions

Variable name	Definition
Capital Ratio	The equity-to-assets ratio. At the county level, we compute the average ratio as the sum of a bank's equity-to-assets ratio multiplied by the bank's proportion of local branches.
Change in HPI (%)	Annual change in the Housing price index from the Federal Housing Finance Agency.
CI loans-to-loans	The ratio of commercial and industrial (C&I) loans-to-total loans. At the county level, we compute the average ratio as the sum of a bank's CI loans-to-loans ratio multiplied by the bank's proportion of local branches.
Community bank	A commercial bank (entity type #10) with total assets less than or equal to $10 billion (constant 2019 US$s). Source FDIC's RIS FTS database.
Distressed county	A county meeting one of the following criteria: 1) unemployment rate > 1.5 times the national unemployment rate; 2) Poverty rate >=20%; 3) Population loss greater than or equal to 10% from the previous to the most recent decennial census.
ΔLn(Employment)	The change in the natural logarithm of employment in the county. Source: Bureau of Economic Analysis
Failure	An indicator equal to one if the loss of a bank in a county (as defined below) is due to a bank failure. Source: FDIC's RIS merger database.
Growth in PCPI	Growth in per capita personal income in the county. Source: Bureau of Economic Analysis
ΔLn (Small establishments)	The change in the natural logarithm of the number of establishments with fewer than 50 employees. Source: US Census' County Business Patterns (CBP).
HFI-deposits	Herfindahl index (HFI) using shares of total deposits by banks in a county. $HFI = \sum_{i=1}^{N} \left[\frac{DEP_{i,t}}{TOT_{c,t}}\right]^2$ DEP- total deposits by bank *i* in county *c*. $TOT_{c,t}$ is the total deposits in county *c*.
High deposit share-community banks	An indicator equal to one for counties with the share of deposits held by community banks in the top tercile of the distribution in a year and zero otherwise.
Large SBL originations	Total amount of SBL originations between $250K and $1 million (constant 2019 US$ 000s). Source: CRA Disclosure files.
Ln (average wages)	The natural log of the average real wages (wages and salaries divided by total wage and salary employment) in the county. Source: Bureau of Economic Analysis.
Loans-to-assets	The ratio of total loans-to-total assets. At the county level, we compute the average ratio as the sum of a bank's loans-to-assets ratio multiplied by the bank's proportion of local branches.
Loans to other firms	Total amount of SBL originations to firms with revenues > $1 million. Computed as total amount of SBL originations minus SBL originations to firms with revenues < $1 million. Source: CRA Disclosure files.
Loss of community bank	An indicator equal to one if one or more community banks with physical presence (i.e., a full-service branch) in the county in year t no longer operate(s) in the county in year t+1.

Appendix A. Variable definitions. Continued.

Variable name	Definition
Merger/consolidation	An indicator equal to one if the loss of a bank in a county (as defined above) is due to bank closures related to an absorption, consolidation, or merger. Source: FDIC's RIS merger database.
NPL ratio	The ratio of nonperforming loans-to-total loans. At the county level, we compute the average ratio as the sum of a bank's NPL-to-loans ratio multiplied by the bank's proportion of local branches, following Berger et al. (2017).
Personal loans-to-loans	The ratio of consumer loans-to-total loans ratio. At the county level, we compute the average ratio as the sum of a bank's consumer loans-to-loans ratio multiplied by the bank's proportion of local branches.
Population growth	The annual growth in the total population in the county. Source: Bureau of Economic Analysis.
RE loans-to-loans	The ratio of total real estate loans-to-total loans. At the county level, we compute the average ratio as the sum of a bank's RE loans-to-loans ratio multiplied by the bank's proportion of local branches.
SBL originations	Total amount of small business loan originations (constant 2019 US$ 000s). Source: CRA Disclosure files
SBL originations to small firms	Total amount of SBL originations to firms with revenues < $1 million. Source: CRA Disclosure files.
SB Loans %	The ratio of SB loans-to-total loans outstanding based on the call report.
Share of deposits- top 4	Share of deposits in the county by the largest four US banks (Citigroup, JP Morgan Chase, Bank of America, and Wells Fargo). Source: FDIC SOD.
Size	The natural log of the book value of assets.
ΔLn (Small firm employment)	The change in the natural logarithm of employment by small firms with fewer than 50 employees. Source: US Census' Quarterly Workforce Indicators (QWI) dataset.
Total SBL originations	Total amount of SBL originations (for CRA reporting banks) plus the aggregate amount of SBA 7A loans for non-CRA reporting banks.
Underserved county	A county with an urban influence code of 7, 10, 11, or 12, as defined by the Economic Research Service of the U.S. Department of Agriculture.