

Impact of Mobile Banking on Small Business Lending After Bank Branch Closures

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Abstract

We provide new evidence on the substitute role of mobile banking in small business lending after banks close branches. Compared to the matched bank-counties with similar economic conditions and bank financials, small business lending in the treatment counties decreases 0.064 million (equivalent to 18.8%) less after branch closings for banks with mobile apps than banks without mobile apps. The effect is more pronounced in high-income census tracts and for high-rated apps, suggesting that high-income customers and customers whose banks provide better mobile apps are less affected when banks close branches. We do not find a significant impact of having apps on small business lending when banks increase the number of branches. However, the effect of having mobile apps increases with closed branches' years of service. Our results imply that bank branches are still important in providing credit to the local communities. Mobile banking helps preserve the existing customer-bank relationship but cannot reduce information asymmetry.

Keywords: Mobile banking, small business lending, branch closure, financial inclusion.

JEL Classification Codes: G210

1 Introduction

A growing body of research studies how the financial crisis of 2007-2008 and subsequent regulations resulted in a significant decline in small business lending (SBL). Ten years or more before the financial crisis, community banks offering standard commercial loans began to lose their place to large banks as the first choice for small businesses seeking credit. According to [Wiersche and Shane \(2013\)](#), small business loan issuance by banks began to decline consistently during the 1990s. The financial crisis merely accelerated these trends. In the postcrisis period, banking institutions, in particular, were affected by bankruptcies, consolidations and mergers. In response many financial institutions closed bank branches: between 2009 and 2014, 4,821 bank branches were closed.¹

When bank branches close, small business lending becomes very costly because borrowers become physically more distant from lenders, and lenders' cost of collecting information about a potential borrower becomes significantly greater. Therefore, the impact of bank branch closures on small business lending and local economic development has become a recurring concern for policymakers and empirical researchers. For example, [Garmaise and Moskowitz \(2006\)](#) show that neighbors who experienced a reduction in bank competition due to bank mergers are associated with diminished real economic activities such as reduced loan provision, diminished local construction, and lower real estate prices and rents, which together lead to increases in crime. Similarly, [Nguyen \(2019\)](#) finds that merger-related branch closures are detrimental to small businesses' access to credit and lead to slow employment growth within six to eight miles of the closure, suggesting that lender distance still plays an important role in small business lending.

When many financial institutions are cutting costs by closing their least important branches, they are also spending more on digital technologies including big data, cloud computing, smartphones and high bandwidth. The direct consequence is that technology enables every aspect of banking to go online and makes traditional branches less necessary. [Petersen and Rajan \(2002\)](#) suggest that advances in storage technology and computing allow lenders to more easily retrieve and process borrowers' credit records, making lender distance a less important measure of creditworthiness in small business lending. In addition, consumers have also shown

¹[PricewaterhouseCoopers \(2014\)](#)

significantly increased interest in embracing this digital transformation.² The [Federal Deposit Insurance Corporation \(2019\)](#) reports that in 2019, 34% of customers used the mobile app as the primary method of accessing accounts, compared with 9.5% in 2015 and 15.6% in 2017.

The two crucial transformations in the banking industry and the mixed evidence on whether lender distance still plays a role in small business lending motivate us to study whether banks' adoption of mobile apps alleviates the negative effect of bank branch closures on small business lending. Using branch-level (branch here refers to bank-county level) small business lending data between 2005 and 2019, we find that while overall small business lending decreases when banks close branches, the reduction is smaller if banks have mobile apps. We refer to the attenuating impact of having apps as the *cushion effect*. The results are robust to controlling for bank characteristics and varying county-level credit demand. To mitigate the concern that both branch closings and mobile app releases are endogenous, we consider an array of county, bank, and branch-level factors that may cause branch closings in the matching process. Specifically, we match each branch closing event with another branch that does not close during the sample period and has the same binary outcome of having apps upon treatment-branch closing. These results are consistent with those of the full-sample analysis. Furthermore, we explore the heterogeneity of the effect of having apps and observe that the effect is only notable in relatively high-income areas. The effect is also more pronounced for high-rated mobile apps. Finally, we show that having apps does not mechanically increase small business lending. Moreover, the cushion effect can be attributed to preserving the existing bank-customer relationship previously constrained by geographic proximity.

We start our analysis by collecting the release dates of bank mobile apps. We focus on the top 10% of banks with the most branches. Our sample consists of 282 banks that accounted for 45%-62% of US branches between 2005 and 2019. We sourced app release dates from the Apple App Store by scraping apps' web pages. In addition, we scraped app ratings to compute the app quality score, which we use in a cross-sectional analysis. Following [Pierri and Timmer \(2022\)](#)'s technology measurement, we regress the percentage of five-star ratings in a calendar year on bank and year-fixed effects and take the standardized coefficients on the bank-fixed

²In a [survey](#) conducted by Ipsos in January 2021, three in four Americans use their primary banks' mobile apps to manage accounts. JPMorgan Chase's [2021 Digital Banking Attitudes Study](#) reports that "respondents reaffirmed that mobile apps have become their most frequently used banking channel, with 73% of consumers citing usage once a week or more, and 62% citing it is a service they cannot live without."

effects as a proxy for the quality of mobile apps.

Then, we examine the impact of mobile banking on small business lending. We draw small business lending data from the Community Reinvestment Act (CRA). The rich bank-county level data allow us to saturate models with county-year fixed effects, thus alleviating the concern that credit demand in a county may change over time. One concern is that local economic conditions drive branch closure. To address this concern, we first exclude bank-county observations that experienced more than one branch closing during the sample period. In addition, we include factors that may cause branch closing in the matching process, which we elaborate on below.

We find that while banks reduce small business lending in counties where they close branches, the reduction is smaller for banks with mobile apps. The adverse effect of branch closings and the cushion effect of having mobile apps are both economically significant: a county experiences a decline in small business lending of 0.728 million US dollars on average from a bank that prunes branches; the reduction is 0.378 million US dollars less for banks providing mobile banking. In other words, the reduction in small business lending is 51.9% ($0.378/0.728$) smaller for banks with mobile apps than banks without mobile apps.

The identification challenge is that both branch closings and having apps are endogenous and may correlate with each other. To address these endogeneity concerns, we utilize the difference-in-differences (DID) model and the instrumental variable strategy that exploits nonlocal factors that drive banks' decisions to have apps. The first DID identification strategy is to match each branch closure with another bank-county that does not experience branch closure. We include event-bank and event-time fixed effects to make comparisons within the bank mapped to a treatment-control pair and to control for time trends. Essentially, our DID model compares changes in small business lending around closures for banks that have apps at the time of closure to contemporaneous changes in small business lending for banks that do not have apps.

The results from our DID model show qualitatively similar results. For banks with mobile apps, the reduction in small business lending is smaller after branch closings. This magnitude is economically smaller than the baseline results obtained using the full sample. After branch closures, banks with apps experience a 0.064 million smaller decline in small business lending than banks without apps. That is, the reduction in small business lending is 18.8% ($0.064/0.340$)

smaller for banks with mobile apps than banks without mobile apps.

As an additional analysis, we employ instrumental variable strategy wherein we identify instruments for both the adoption of mobile apps and the branch closures. To gauge mobile app adoption, we leverage the variations in a bank’s exposure to mobile wireless coverage across the counties where it operates branches. The majority of banks in our sample are large commercial banks with branches spread across multiple markets, and their operations are dispersed across various counties. Therefore, it is unlikely that our instrument, an aggregate metric determined by all the counties in which a bank operates, is correlated with local economic conditions. For branch closures, we utilize the geographic dispersion of a bank’s branches within a county as an instrument. The more concentrated a bank’s branches are within a county, the more likely the bank will close some of those branches. We employ two-stage-least-squares analysis and find that location-driven branch closures, coupled with having apps, a consequence of higher bank-level exposure to mobile wireless coverage in other counties, results in a 0.374 million smaller decrease in small business lending following the closures of branches.

To investigate which segments exploit the benefits of bank mobile apps, we segment small business lending by borrowers’ census tract income level. Mobile banking usage varies across income level, with low-income people having less access to technologies such as smartphones and home broadband.³ Hence, we expect the effect of having apps to be more pronounced in high-income areas than in low-income areas. Consistent with this notion, we find that the cushion effect of having mobile apps is evident among borrowers residing in relatively high-income census tracts. In upper-income census tracts, small business lending shows low elasticity to branch closure, indicating considerable financial resilience among the high-income population.

In addition to borrowers’ income levels, we also analyze the heterogeneity of the effect based on app quality. Using the mobile app quality score derived from app ratings, we find that the positive impact of having apps is amplified when apps are of high quality. The cross-sectional analyses further support our main findings by showing that the effect differs with respect to access to mobile apps and satisfaction with them.

Why might mobile apps alleviate branch closings’ negative effect on small business lending? We consider banks’ developing mobile banking as a coarse representation of their commit-

³A [Pew Research Center Survey \(2021\)](#) reports that households with an annual income of \$30k or below are less likely than households with an annual income between \$30k and \$99.999k or of \$100k and more to have a smartphone, laptop, and home broadband. Moreover, the technology divide is persistent from 2019 and 2021.

ment to developing financial technology. In theory, possessing superior technology may relieve frictions for both lenders and borrowers. Banks face information frictions which may induce adverse selection or impede the extension of credit to qualified borrowers. Financial technology complements bank branches in collecting and assessing different sources of information, empowering banks to provide credit to new customers. We test the first possibility by exploiting the situations where banks increase the number of branches. If tapping into mobile banking improves the lending process and helps build new bank-customer relationships, we should observe a greater increase in small business lending for banks with an app. We do not find such evidence. The results show that having apps does not further increase small business lending in the affected counties, suggesting that mobile banking does not mitigate information frictions.

Customers encounter externalities when they opt to switch lenders. Since most information garnered through branch visits is considered soft and nontransmissible, it is costly for customers to start a new relationship with lenders. Mobile banking serves as a virtual alternative to bank branches and taps into the information stored in closed branches to continue offering credit to a fraction of current customers. We test the second channel by examining whether the effect of having apps varies with information asymmetry. If easy access to bank apps alleviates this externality, we should observe a stronger cushion effect of having apps in areas where the information asymmetry between borrowers and banks is low. We measure information asymmetry using closed branches' years of service. We argue that the longer a branch serves a community, the lower the bank-borrower information asymmetry is. The results show that the cushion effect is more pronounced when closed branches served communities longer. That is, the benefits of having apps rely on there being low information asymmetry between borrowers and banks.

The overall results suggest that mobile banking cushions the shock induced by branch closure by bridging the gap between lenders and borrowers. Possessing better mobile apps lessens the catastrophic consequences of branch closings in terminating distributing loans to existing borrowers on whom banks have an informational advantage. The asymmetric effect of having apps and its varying effect on information asymmetry indicate that mobile banking cannot reduce information asymmetry as branches do. In other words, while the trend is shifting towards a more digitalized approach in the banking industry, bank branches are still important

in the small business loan market.

The paper relates to the literature on geographical proximity in lending. Following branch deregulation, bank branches sprung up in the U.S., substantially decreasing the effort and time consumers spend traveling to lenders. Geographical proximity, however, has opposing effects on consumers' financial well-being. On the one hand, proximity helps lenders monitor and collect information at a lower cost, increasing borrowers' chances of obtaining loans (Mian, 2006; Sufi, 2007; Agarwal and Hauswald, 2010; Gilje et al., 2016). On the other hand, lenders may exploit borrowers using the precise information they obtain from a closer distance (Degryse and Ongena, 2005; Hauswald and Marquez, 2006). The two effects lie in the assumption of borrowers' externalities when switching lenders. It is costly to do so if the lenders' private information is not transmittable (see Xu et al., 2020) or if the local credit market is less competitive such that competitor banks do not have strong incentives to provide a comparable loan contract. Consistent with the literature (Ergungor, 2010; Nguyen, 2019), we show that access to branches remains economically important in shaping banks' credit allocation. However, mobile banking diminishes the importance of proximity such that the credit supply of banks with mobile apps is less sensitive to branch closings.

Our work also relates to technology adoption in banks. The literature documents the impact of technology on banks' financial performance: Technology strengthens banks' resilience to economic shocks (Pierri and Timmer, 2022) and boosts banks' profitability by improving productivity (Petersen and Rajan, 2002) and increasing demand for bank services (Oliver and Fumas, 2008); in contrast, technology investments decrease banks' productivity (productivity paradox) as decompositions of technology exhibit mixed results (Beccalli, 2007). Instead of examining the aggregate effect of technology as a whole, we zoom in and focus on emerging mobile banking and study how having mobile apps affects banks' loan decisions. Our work supplements the mobile banking literature by documenting the digitalization of the banking industry and how doing so helps preserve the bank-borrower relationship that previously required the physical presence of branches.

Finally, the paper provides the latest regulatory implications on how financial innovations affect financial access. Financial innovations, such as the emergence of alternative lenders, expand financial access by providing credit to underserved customers (Erel and Liebersohn,

2022). Most papers, however, emphasize the financial access of underbanked or unbanked populations, while ours concentrates on banks' marginal customers. Unlike the previous findings that low-income households benefit the most from technologies (e.g., FinTech lenders), our paper shows that high-income populations gain more advantages than other income groups from efficient mobile banking.

The remainder of the paper proceeds as follows, Section 2 describes the data sources and main variables. Section 3 describes the identification challenges and strategy. Section 4 presents the empirical results. Section 5 concludes the paper.

2 Data and Variables

We focus on the top 10% banks with the most branches in the 48 contiguous U.S. states, that is, banks with at least ten branches. Our sample contains 282 banks and accounts for 45% and 62% of US bank branches between 2005 and 2019. We use geographic information on bank branches obtained from the Summary of Deposits (SOD) to match the bank-county-level small business lending collected from the CRA. Next, we scrape Apple App Store to obtain bank app release dates and construct our app quality score. We use data from Call Report to compute bank variables. Finally, we collect county characteristics from several sources: housing price data from Zillow, the population from the U.S. Census Bureau, and the unemployment rate from the Local Area Unemployment Statistics (LAUS) program of the U.S. Bureau of Labor Statistics. The final sample consists of 84,299 observations for 282 banks, spanning 2,600 counties in the U.S. between 2005 and 2019.

2.1 Bank Mobile Apps

Our data on bank app release dates come from scraping each app's web page on the Apple App Store.⁴ Among the 282 banks in the sample, 280 banks had iOS apps (apps hereinafter) in 2019. Panel (a) of Figure 1 depicts the number of bank apps launched between 2005 and 2019. Seventy-five percent of the 282 banks in our sample launched mobile apps before 2014, and this

⁴The Apple App Store is one of the largest mobile application platforms in the world (see <https://www.grandviewresearch.com/industry-analysis/mobile-application-market>). Although iOS users only represent a fraction of bank customers, app release time, market penetration, and user satisfaction on one platform are indicative of those on other platforms, such as Android.

proportion rose to 87% in 2016. Figure 2 presents maps illustrating the geographical distribution of bank branches with mobile apps in 2009, 2014, and 2019. Clearly, mobile banking coverage has progressively expanded over the years. Moreover, there is considerable variation in the proportion of branches providing mobile banking across counties. We incorporate county-year fixed effects to account for county-level factors that may influence small business lending.

We create an indicator *Have_App* that equals one for time periods during and after a bank launched an app and zero otherwise. Note that for apps that have been delisted or renewed, we cannot access historical information. For example, if a bank released its first consumer app in 2012 but delisted it in 2014 and launched a new app the following year, we identify the release year as 2015. To validate the year of app release, we randomly selected 10% of the banks in the sample and searched for app release announcements and media exposure. The search results show that our app release timeline is highly consistent with the app’s media appearance.

We then explore the rich data on daily ratings in the Apple App Store to compute the app quality score and categorize banks into high- and low-quality groups for a cross-sectional analysis in Section 4.2.2. We attached a screenshot of app reviews for Pacific Western Bank in Appendix F.1. We retrieved daily app ratings between 2008 and 2019 because 2008 was the earliest year in which our target banks launched their mobile apps, and 2019 was the most recent year in which we can access CRA data.

To derive the app quality score, we first calculate the share of the highest rating (5 stars) in a year. Similar to the Pierri and Timmer (2022) estimation method, we regress the year-level percentage of 5-star ratings on bank and year fixed effects and take the standardized coefficients on bank fixed effects as banks’ app quality scores. Specifically, we take the standardized coefficient ω_i in Equation 1 to measure app quality.

$$\%Rating\ 5_{it} = \omega_i + \phi_t + \mu_{it} \quad (1)$$

Our estimation takes the average of banks’ app qualities between 2005 and 2019. Compared to using the percentage of or the count of 5-star ratings, the fixed effect estimation smooths the unexplained fluctuations in bank app ratings over the years. A higher app quality score indicates a more efficient app in meeting bank customers’ needs for financial service

We list the top 10 and bottom 10 banks based on estimated app quality scores in Ap-

pendix A.2. To address the endogeneity of the app quality score, we create a dummy variable *High_Quality* that equals one for banks whose app quality score is above the median, and zero otherwise.

2.2 Bank Branches

We use the SOD from FDIC to extract geographic information about bank branches. For each branch, we have the address, parent institute name and ID, unique branch ID that does not change when transferring ownership⁵, and yearly deposits at the branch and institute levels. We focus on full-service branches that are not bank headquarters.⁶ In a county, a bank had an average of two branches between 2005 and 2019 with mean deposits of 117.6 million USD.

We consider that a bank reduces branches in a county if the total number of branches of a bank decreases relative to the previous year. To capture this, we create a dummy variable *Post_Branch_Drop* that equals one during and after branch closure and zero otherwise. *Post_Branch_Drop* is a dynamic variable that captures bank-county-level variations over time. In our sample of 282 banks, we observe 4275 branch closing events between 2005 and 2019. Note that many banks experienced multiple branch closings within the same county over the sample period. Panel (a) of Figure F.2 in the Appendix displays the frequency of branch closings per bank-county. Out of the total sample, 2428 bank-counties had one closing event, followed by 940 bank-counties with two closings, and 463 bank-counties with three closings. We remove bank-counties that experienced multiple branch closings to partially relieve the concern that consecutive branch closings may correlate with changes in local credit demand.

Furthermore, it is noteworthy that some bank-counties experience both branch closures and branch openings. For the 2428 bank-counties that experienced only one branch closing event in the sample period, 1,609 did not open any new branches, 521 had one branch opening event, and 173 had two branch opening events, as shown in Panel (b) of Figure F.2. It becomes challenging to disentangle the effects on small business lending during the overlapping period of branch closings and openings. To address this issue, we restrict the analysis to branch closing

⁵Some branches existed earlier and later but did not appear in between. Since the branch ID does not change over any ownership transfer, we refill the disappearing branches if they show up later with the same address and branch ID.

⁶FDIC categorizes full-service branches into three groups: brick-and-mortar office, retail office, and home banking. The first two types fit our context, and we calculate a bank's full-service branches as the sum of the two.

events that do not coincide with an expansion of branches within the same sample period.

After these adjustments, we are left with 84,299 bank-county observations, covering 1,609 branch closings that occurred between 2005 and 2019. Panel (b) of Figure 1 displays the frequency of branch closing events, revealing a clear upward trend: the number of bank-county observations experiencing a decrease in the number of branches rose from 47 in 2006 to 206 in 2019. Additionally, Figure 3 maps the geographic distribution of branch closings in the U.S. in 2006 and 2019. We observe that although branch closings became more evenly distributed over time, they were initially less likely to occur on the West Coast than in other regions during our sample period.

2.3 Lending Activity

We measure banks' small business lending activities using CRA data. The data provide the bank-county level number ($SBL (\#)$) and dollar amount ($SBL (\$)$) of small business loans; based on these data, we calculate the growth rate ($SBL (\$) \text{ growth rate}$) and the natural logarithm ($Ln(SBL (\$))$) of small business loans in dollars. We also decompose these figures according to census tract income levels, which we use in a separate analysis to examine the heterogeneity of the main result.

The summary statistics about small business lending are shown in Panel B of Table 1. On average, banks extend credit to 61 loan applications in a county per year, amounting to 5.011 million US dollars. A large proportion of credit flows to moderate- and upper-income census tracts: 2.426 and 1.416 million US dollars in the middle- and high-income areas, respectively, versus 0.213 and 0.884 million in the low- and moderate-income areas, respectively.

2.4 Other Controls

We retrieve data from Call Report to compute bank characteristics, including the natural logarithm of total assets ($Ln(Asset)$) and wages ($Ln(Wage)$), the share of loans ($Loans/Assets$), equity ($Equity/Assets$), and net income (ROA) over assets. Together with the branch deposits and the number of branches in a county, we use these seven bank characteristics as controls in some analyses. We present the summary statistics in Panel A of Table 1.

Our county median housing price (HPI) data come from the Zillow Home Value Index. For

the population (*Population*) by county, we use data from the U.S. Census Bureau. Our county-level unemployment rate (*Unemployment_Rate*) data are obtained from the U.S. Bureau of Labor Statistics. In addition, we calculated the sum of deposits across all FDIC-insured branches (*Tot_Deposit_County*) and the number of FDIC-insured branches (*Tot_Branch_County*) in a county using SOD data. When matching counties, we include the total amount (*SBL_County* (\$)) and the number of small business loans (*SBL_County* (#)) in a county obtained from CRA data as additional controls. The county-level summary statistics are outlined in Panel C of Table 1.

3 Research Design

In this section, we study the cushion effect of having mobile apps when banks close their branches by conducting an OLS analysis. To address the endogeneity concern that banks voluntarily decide whether to adopt mobile apps and/or close branches, we construct a DID model, followed by an instrumental variable strategy as a secondary test to strengthen our analysis.

3.1 Baseline

To examine the impact of banks' adoption of mobile apps on small business lending after branch closings, we use the following OLS regression:

$$SBL_{i,c,t} = \alpha + \beta_1 Post_Branch_Drop_{i,c,t} + \beta_2 Have_App_{i,t} + \beta_3 Post_Branch_Drop_{i,c,t} \times Have_App_{i,t} + \eta \Gamma_{i,(c),t} + \kappa_i + \delta_{c,t} + \epsilon_{i,c,t} \quad (2)$$

where $SBL_{i,c,t}$ is an array of dependent variables representing the small business lending activities of bank i in county c in year t . $Post_Branch_Drop_{i,c,t}$ is a bank-county-level dummy variable that equals one if bank i reduced the number of branches in year t relative to the previous year in county c . $Have_app_{i,t}$ is a bank-level dummy variable capturing whether bank i had a mobile app in year t . We include a set of time-varying bank- and bank-county characteristics including the dollar amount of total assets in logarithm, the ratio of loans to total assets, the ratio of equity to total assets, return on total assets, wages and salaries in

logarithm, a bank’s deposits in millions in a county, and a bank’s number of branches in a county. In addition, the specification includes bank and county-year fixed effects. The county-year fixed effects control for changes in local economic conditions, absorbing the unobserved county-level variation.

The coefficient β_3 on the interaction term of $Post_Branch_Drop_{i,c,t} \times Have_App_{i,t}$ identifies the marginal effect of having mobile apps on small business lending after branch closings, by additionally accounting for observable characteristics.

3.2 Difference-in-Differences

Our main challenge in identifying the causal impact in this setting is that both the decisions of branch closings and launching mobile apps are endogenous. To address this concern, we consider an array of factors that may cause branch closings in the bank-county-level matching process. Specifically, we compare changes in small business lending due to branch closures among banks with mobile apps and banks without mobile apps at the time of closure.

The matching process consists of two steps. First, for each of the 1,609 branch closing events, we select three potential bank-county controls that do not experience branch closures but are closest on seven ex ante county level and two bank-county level characteristics. These characteristics are the unemployment rate (*Unemployment_Rate*), the natural logarithm of median housing pricing (*HPI*), the natural logarithm of population (*Population*), the natural logarithm of total deposits across all FDIC-insured branches (*Tot_Deposit_County*), the natural logarithm of the total number of FDIC-insured branches (*Tot_Branch_County*), the natural logarithm of the amount and number of small business loans (*SBL_County (#)* and *SBL_County (\$)*), the proportion of a bank’s deposits in a county to its total deposits (*Share_Deposits*), and the number of a bank’s branches in a county to its total number of branches (*Share_Branch*).⁷

To select these potential control bank-counties for each branch closing event, careful con-

⁷Tracing the factors contributing to systematic branch closures across cities proves challenging, because the affected areas exhibit little commonality beyond experiencing branch closures ([National Community Reinvestment Coalition 2022 Report](#)). However, the same report highlights three crucial patterns that aid in identifying branches with a high probability of facing shutdown: (1) branches located in areas with an increasing population; (2) unprofitable branches, specifically those attracting fewer deposits; and (3) branches situated in competitive environments. To address these potential reasons for branch closings, we incorporate variables one by one, including the natural logarithm of a county’s population, a bank’s share of deposits in a county relative to its total deposits, and the dollar amount and the number of small business loans in a county. Furthermore, to account for local economic condition, we incorporate the unemployment rate and the natural logarithm of housing price into the matching process.

sideration must be given to all the factors involved. Bank branch closures are attributable to bank consolidation, high overhead expenses, shifts toward digital channels, and population changes (Hinton et al., 2017). With that in mind, small regional banks are more likely to shutter branches than large interstate banks due to limited market share and fewer resources available to adapt to evolving business environments (Edlebi et al., 2022). Richardson et al. (2017) and Tranfaglia (2018) show that geographic location also plays a role in branch closure decisions in which branch closings cluster in suburban areas, characterized by a low population and moderate housing values.

Next, from the three potential controls, we match the treated closed branch with one control that shares similar having app status, i.e., whether the bank has an app, but has not experienced branch closings. For example, if the closed branch belongs to a bank that does not have an app, we will match it with a control branch whose bank does not have an app in the branch-closing year. Similarly, if the closed branch belongs to a bank with an app, we match it with one control bank-county that shares similar county and bank characteristics and has an app in the branch closing year. If more than one control (out of three) shares a similar having app status, we pick the one with the closest Euclidean distance, determined by the seven ex ante county- and two bank-county-level characteristics.

Following this two-step matching process, we identify 145 bank-county pairs of branch closings between 2005 and 2019. Table 3 reports summary statistics of the county and bank characteristics between the control and treatment groups before and after matching. Prior to the two-step matching, Columns 1 and 2 suggest that treatment branches tend to be located in counties with higher unemployment rates and lower median housing prices, consistent with prior literature showing that the local economy plays an important role in bank branch closures (Ergungor and Moulton, 2011). Moreover, Columns 1 and 2 of Table 3 reveal that counties with relatively larger populations, more deposits and branches, and greater small business loan demand are more likely to face branch closings, reconciling with Richardson et al. (2017) and Breitenstein and McGee (2015)’s finding that branch closures have been concentrated in metropolitan areas. Although descriptive in nature, this table points to the importance of carefully selecting the control group. After the careful matching process, differences in the treatment and control groups along these dimensions are no longer significant, as shown in

Columns 3 and 4 of Table 3. We discuss other matching considerations, such as altering the number of nearest neighbors in step one in Section 4.1.2.

After successfully matching the treatment and the control groups on observables, we use the following DID equation to remove common time trends:

$$SBL_{i,c,t,e} = \alpha + \beta_1 Post_Branch_Drop_{i,c,t} + \beta_2 Have_App_{i,t} + \beta_3 Post_Branch_Drop_{i,c,t} \times Have_App_{i,t} + \zeta_{e,i} + \gamma_t + \epsilon_{i,c,t,e} \quad (3)$$

where index i refers to the bank, c denotes the county, t indicates the event time, and e refers to the event pair. The dependent variables $SBL_{i,c,t,e}$ include small business lending in millions of dollars, its growth rate, and the logarithm of small business lending. $Have_app_{i,t}$ is an indicator that equals one if bank i had a mobile app in event year t . $Post_Branch_Drop_{i,c,t}$ is a dummy variable that equals one when bank i reduced its branch network size in county c during event year t .

The coefficient of interest is β_3 which captures how small business lending reacts to having apps after banks close branches. We incorporate event-bank fixed effects, represented by $\zeta_{e,i}$, to account for time-invariant changes in small business lending among banks. Additionally, γ_t denotes the event-time fixed effects, which control for the changes in small business lending in the control bank-counties over time. We cluster standard errors at bank level.

When utilizing the difference-in-differences model, it's important to examine the parallel trend assumption, which states that the difference in small business lending between treatment and control groups should be constant over time. Therefore, we compare small business lending between two sets of treatment and control bank-counties surrounding branch closures. One set consists of treatment and control bank-counties with mobile apps when experiencing branch closures, while the other set includes treatment and control bank-counties without mobile apps during the year of branch closures. We augment the regression specification of Equation 3 with five different indicators for (-4,1) event windows surrounding the branch closing events.

$$\begin{aligned}
SBL_{i,c,t,e} = & \sum_{\substack{t=-4 \\ t \neq -1}}^{+1} \lambda_t Year_t \times Treatment_{i,c} \times Have_App_{i,t} + \\
& \sum_{\substack{t=-4 \\ t \neq -1}}^{+1} \phi_t Year_t \times Treatment_{i,c} + \zeta_{e,i} + \gamma_t + \epsilon_{i,c,t,e}
\end{aligned} \tag{4}$$

$Treatment$ equals one for bank-counties that experienced branch closings and zero for matched bank-counties. The coefficient λ represents the dynamic changes in small business lending between the control and treatment bank-counties with mobile apps, while ϕ captures the dynamic changes in small business lending between the control and treatment bank-counties without mobile apps. The difference between λ and ϕ provides the marginal impact of having apps on small business lending around branch closures. This equation resembles our DID model specified in Equation 3, with the modification being the substitution of the post-branch-closing indicator $Post_Branch_Drop$ with the interaction terms of treatment indicator $Treatment$ and five event-time indicators $Year_t$.

The results, detailed in Table 5, show that the differences in small business lending between the control and matched groups are statistically insignificant before branch closures, regardless of whether bank-counties have mobile apps. Notably, lending activities exhibit a decline only during the year of branch closures. Overall, these findings offer evidence supporting the causal impact of having apps on small business lending following branch closures.⁸

3.3 Robustness

As a supplementary test to bolster our analysis, we implement an instrumental variable strategy wherein we identify one instrument for $Have_App$ and another for $Post_Branch_Drop$.

3.3.1 IV for $Have_App$

We leverage the mobile wireless coverage scaled by the share of deposits as an instrument for $have_app$. Similar instruments have been applied and validated in other studies. For example, in investigating the impact of banks' IT spending on the local mortgage market, [Cuesta et al.](#)

⁸The parallel trend assumption is still satisfied when we make $Have_App$ a constant variable. It takes a value of one for treatment bank-counties with mobile apps during branch closures and zero for those without apps. In the control group, the $Have_App$ value is determined based on the corresponding treatment bank-counties' branch closing year as a reference point. See Online Appendix Table [OA.3](#).

(2023) utilize the deposit-weighted housing price as an instrument for banks' IT adoption. Their rationale rests on the assumption that higher exposure to housing prices could induce exogenous variation in the local mortgage market.

To be an instrument, a variable must affect banks' decision to adopt mobile apps without concurrently altering factors that could impact the demand or supply of small business lending. In other words, an instrument should leave small business lending unaffected if the status of *have_app* is held constant. One possible instrument is banks' exposure to mobile wireless coverage. Specifically, for bank i operating in county j in year t , its exposure to mobile wireless coverage can be defined as:

$$avg_mobile_cov_{i,t} = \sum_j mobile_cov_{j,t} \times \frac{Deposits_{i,j,t}}{Deposits_{i,t}} \quad (5)$$

where $mobile_cov_{j,t}$ represents the mobile wireless coverage of county j in year t , $\frac{Deposits_{i,j,t}}{Deposits_{i,t}}$ denotes the share of bank i 's deposits in county j relative to the bank's total deposits in year t (referred to as *Share_Deposits*)⁹. Therefore, the variable *avg_mobile_cov* captures bank i 's exposure to mobile wireless coverage in year t across all counties where it operates, with weighting based on the deposit share of bank i in county j relative to its total deposits in that particular year t .

To measure county-level mobile wireless coverage, we combine two sources of administrative data. Since the enactment of the *Broadband Data Improvement Act* in October 2008, broadband service providers have been required to file reports biannually, in June and December, to the states where they operate, detailing information on the availability, speed, and location of broadband service. These data have been publicly available since 2010 and were used in the *State Broadband Initiatives* (SBI) program administered by the National Telecommunications & Information Association (NTIA). The SBI program ended in 2015, when the most recent broadband data were collected as of June 2014. After that, the responsibility for data assistance shifted to the *Federal Communications Commission* (FCC).

We obtain provider-census-block-level broadband coverage data for the years between 2010 and 2014 from the NTIA. First, we filter the records with the technology code (column "TransTech") set to "80," indicating the technology of terrestrial mobile wireless. To align these data with

⁹*Share_Deposits* is one of the factors used in the matching processing outlined in Section 3.2

other sources, we compute the average percentage of census block coverage at the county level across providers. Over the period from 2010 to 2014, the average coverage by mobile wireless networks in a county was 93.648%, with a standard deviation of 7.394%, as shown in Panel A of Table A.4.

For the timeframe spanning from 2015 to 2019, we incorporate mobile deployment data from the FCC.¹⁰ This dataset contains mobile wireless coverage details for different technologies, where codes such as “83” represents LTE and “85” denotes CDMA, in each census block.¹¹ Since we do not focus on one specific mobile wireless technology, we use the column labeled “ANY,” which indicates the percentage of an area covered by at least one type of technology in a census block. Similar to the aggregate method applied to the NTIA data, we calculate the average coverage across census blocks to derive county-level coverage. Panel A of Table A.4 presents the summary statistics for *mobile_coverage* during 2015-2019. The average coverage rate is 99.525%, reflecting a 5.877% increase compared to the period between 2010 and 2014. The standard deviation is 1.811%, accounting for a quarter of the variation between 2010 and 2014.

Finally, we aggregate *mobile_cov* across the two time frames and weight the data by the share of deposits to obtain the instrument, *avg-mobile_cov*. Between 2010 and 2019, the banks’ average exposure to mobile wireless coverage was 97.437%, with a median value of 98.814%.

The instrument works that broader coverage of the mobile wireless network increases the likelihood of customer demand for mobile banking, consequently accelerating the development of bank mobile apps. Furthermore, given that our instrument is an aggregate metric considering all counties where a bank has branches, it is unlikely that any omitted variables affecting the demand for small business loans in one county will also affect other counties.

Two possible scenarios could challenge the exogeneity condition. First, if a bank’s branches do not disperse across counties, the variable *avg-mobile_cov* might be driven predominantly by the mobile coverage of a single county, potentially introducing correlation with local credit demand. However, the banks in our sample are primarily large commercial banks operating across multiple markets. As depicted in Table 1, the average share of branches in a county relative

¹⁰A notable shift in reporting the data post-2014 is the separation of mobile deployment data from fixed broadband deployment data.

¹¹Technology codes are defined by the FCC. https://broadbandusa.ntia.doc.gov/sites/default/files/2021-06/NBAM%20Data%20Submission%20Guidelines_0.pdf

to a bank’s total number of branches is 3.7%, with 75% of banks operating 3.3% of their total number of branches per county. Additionally, the average fraction of deposits *share_deposits* is 3.7%, and 75% of branches contribute to 2.8% of a bank’s total deposits in a given year. These statistics imply a high degree of diversification in branch operations across counties. Second, even when banks operate in multiple counties, it is possible for these counties to be internally connected and simultaneously impacted by the same factors. In such situations, a county’s credit demand may be jointly influenced by the dynamics of other counties. However, we consider this scenario unlikely. Not only are bank branches geographically scattered throughout the U.S., but there is also significant variation in mobile coverage across counties.

3.3.2 IV for *Post_Branch_Drop*

We employ the geographic dispersion of a bank’s branches within a county as an instrument for *Post_Branch_Drop*. The rationale behind selecting this instrumental variable is that if a bank’s branches are more concentrated (spread out) within a county, it is more (less) likely for the bank to close a few branches due to a highly overlapping operational network, potentially lowering marginal profits. However, the geographic location is unlikely to impact small business lending through any economic factors.

The instrumental variable for *post_branch_drop* is constructed as follows: First, we compute the centroid of a bank’s branches within a county for a given year using branch-level geographic data from the Summary of Deposits. Specifically, we compute the average longitude and latitude across all branches. Next, we calculate the shortest distance between the bank’s branches and the centroid using the Haversine formula.¹² Finally, we take the natural logarithm of the average of all distances plus one to derive the instrumental variable, $\ln(\text{avg_distance}+1)$. The summary statistics are presented in Panel A of Table A.4.

¹²The Haversine formula helps in determining the distance between two points on a sphere based on their longitudes and latitudes. In R, this calculation is facilitated by the “distHaversine” function.

4 Results

4.1 Impact on Small Business Lending

In this subsection, we document the empirical evidence of the cushion effect by presenting the results of OLS regression. We subsequently provide evidence against underlying economic differences and the correlation between the app release window and the branch closing window driving our results. Finally, we employ the instrumental variable strategy to provide robustness.

4.1.1 Baseline Results with the Full Sample

Panel A of Table 2 reports the estimates of Equation 2. In Columns 1-3, we use different proxies for small business lending as the dependent variable: the bank-county level of small business lending in millions of dollars, the growth rate of small business lending in dollars, and the natural logarithm of small business lending.

Using Column 1 with the amount of small business lending as our baseline implies that banks decrease small business lending by 0.728 million dollars after closing branches. However, the reduction is 0.378 million dollars smaller if banks have mobile apps. To better understand the magnitude in context, consider that the average lending amount for a bank in a county is 5.011 million dollars per year. This finding suggests that the average cushion effect of having mobile apps represents approximately 7.5% ($0.378/5.011$) of a bank’s small business lending in a county.

In Columns 2-3, we use the growth rate of small business lending and the natural logarithm of small business lending in dollars as the dependent variables. We find qualitatively similar results.

To alleviate the concern about “bad control variables”¹³, we follow the same scheme, reproduce our results by excluding bank controls and adding year fixed effects to control for changes in banks over time. We present the results in Panel B of Table 2. We find that the main results still hold.

¹³In a nonexperimental setting, it is likely to include control variables that are outcomes of the independent variable(s) or dependent variable, leading to biased estimates of the casual effect. (Whited et al., 2021 detail the recognition of good and bad controls. <https://publications.aaahq.org/accounting-review/article-abstract/97/3/395/4425/Out-of-Control-The-Over-Use-of-Controls-in?redirectedFrom=fulltext>)

The complete sample includes bank-counties with and without branch closing events. Next, we restrict our sample to bank-counties that experienced branch closings to directly compare the changes in small business lending between two bank-counties that both experienced branch closings, one had mobile apps and the other did not. Panel C of Table 2 reports the results. We perform the analysis for both the baseline (similar to Panel A) in Columns 1-3, and the bad control design (similar to Panel B) in Columns 4-6. The estimates of the impact of having apps using the restricted sample are similar to those derived from the full sample.¹⁴

4.1.2 DID Analysis

Note that the above results may suffer from the concern that the decision to close branches is endogenous. Therefore, we estimate the baseline model using the matched data described in Section 3.2 to estimate Equation 3. The summary statistics of the differences in characteristics between the treatment and control bank-counties are reported in Table 3. We do not observe any significant differences between the treatment and control groups. Table 4 presents the baseline results using the matched sample.

The coefficient of the interaction term β_3 represents the differential effect of having mobile apps on the small business lending of the treatment versus the control bank-county after bank branch closure. The results are qualitatively similar to the results in Table 2. The baseline case, shown in Column 1, implies that a branch closing event is associated with a decrease of 0.34 million USD in small business lending in the affected county. Having mobile apps, however, helps banks lessen the reduction by 0.064 million USD.¹⁵

To evaluate the sensitivity of our baseline results against the choice of the number of nearest neighbors, we use different pool sizes of candidate control bank-counties and show summary statistics in Panel A of Table A.3 and main results in Panel B. Choosing a larger pool size increases the chance of surviving the further restrictions in the second step of the matching. However, it compromises the closeness between the control and treatment groups.

In Column 1 of Panel B of Table A.3, we find that the coefficients of the interaction term across Panels B1-B2 continue to be statistically significant and economically meaningful, rang-

¹⁴Our findings remain consistent even after defining the variable *Have_App* as a constant. Specifically, *Have_App* is assigned a value of one for bank-counties with mobile apps during the year of branch closures, while it is zero for bank-counties without apps during branch closures and those without any branch closures. For more details, refer to Online Appendix Table OA.1.

¹⁵Our results still hold when we make *Have_App* a constant variable. See Online Appendix Table OA.2.

ing from 0.212 to 0.347 million dollars. In Column 2 of Panel B, the coefficient on the interaction term is statistically insignificant. One possible explanation is that large scaling (small business lending in the base year) results in relatively small changes in the dependent variable. Alternatively, we use the natural logarithm of small business lending as a dependent variable to represent changes in lending activities in Column 3. These results are consistent with the previous finding that small business lending decreases less for banks with an app than for banks without an app.

4.1.3 IV Analysis

This subsection provides an additional analysis utilizing the deposit-weighted average of mobile wireless coverage as an instrument for banks' adoption of mobile apps, and the geographic dispersion of bank branches in a county as an instrument for branch closures. We follow a two-stage least squares (2SLS) approach by separately regressing *Have_App* and *Post_Branch_Drop* on their corresponding instruments, while controlling for a set of variables and fixed effects. In the second stage, we regress small business lending on the fitted value of *Have_App* and *Post_Branch_Drop*, and report the results in Panel B of Table A.4.

Columns 1 and 2 show the results of the first stage, whereas Columns 3-5 show the instrumental variable estimates. In Column 1, we observe that a 1% increase in *avg_mobile_cov* corresponds to a 0.9% increase in the likelihood of adopting mobile apps. The F-statistic of 67.81 surpasses the threshold of 10, indicating that *avg_mobile_cov* is not a weak instrument. In Column 2, the coefficient on $\ln(\text{avg_distance}+1)$ is negative and statistically significant at the 10% level, suggesting that bank-counties with a more concentrated operation network are more likely to experience branch closures. Additionally, $\ln(\text{avg_distance}+1)$ passes the weak IV test, with an F-statistic of 24.15. Columns 3-5 exhibit the main estimates, aligning with the direction of the OLS estimates. Using Column 3 as the reference, the findings suggest that the adoption of mobile apps and the closure of bank branches, attributed to a greater exposure to mobile wireless coverage in other counties where banks operate branches and a shorter distances between a bank's branches within a county, lead to a decrease in local small business lending by 1.053 million dollars. Nevertheless, for banks equipped with apps, the decline in small business lending is mitigated by 0.374 million dollars compared to banks without apps.

This cushion effect translates to a noteworthy 35.5% ($0.374/1.053$) smaller reduction in small business lending following branch closings.

In summary, our results are in line with the literature demonstrating the detrimental impact of branch closings on small business lending. More important, we show the ability of mobile banking to cushion against adverse effects.

4.2 Heterogeneity

In this subsection, we test the heterogeneity of our results. We study how borrowers' census tract of residence income level and app design efficiency may affect our results.

4.2.1 Borrowers' Income Level

Uneven access to technological innovation, such as mobile banking, leads to an unequal distribution of benefits. Household income levels significantly contribute to the “digital divide.” High-income households have greater access to technology and reap more benefits than low-income households. Therefore, we expect to observe a weaker cushion effect in low-income areas and a stronger effect in high-income areas.

We use small business lending in census tracts aggregated at the county level. The census tracts are smaller geographic entities within counties, and are divided into four income groups by the U.S. Census Bureau: low, moderate, middle, and upper, depending on the median household income of the census tract and a fraction of the median income in the decennial metropolitan statistical areas. If there is more than one low-income census tract in a county, we sum up the small business lending in two census tracts as the lending for the low-income census tract in the county. Following this, we have the same number of observations across regressions by income level.

Table 6 shows the results. The dependent variable in Columns 1-4 is small business lending in millions of dollars in low, moderate, middle, and upper census tracts aggregated at the county level. In Column 1, we find that branch closings are connected with a decrease in small business lending of 0.005 million dollars in low-income census tracts. Furthermore, having apps does not significantly impact lending activities in low-income areas, suggesting that people living in low-income areas enjoy fewer benefits from mobile banking.

Similar effects of branch closings and bank apps are found in moderate-income census tracts, as in Column 2 of Table 6. In Column 3, the coefficient on *Post_Branch_Drop* remains negative and statistically significant at the 1% level while the coefficient on the interaction term $Post_Branch_Drop \times Have_App$ is positive and becomes significant at the 1% level. The results indicate that small business lending in relatively high-income areas is sensitive to whether banks have mobile apps. People residing in middle-income areas may have adequate access to mobile devices and thus are less affected by local branch closings.

Column 4 of Table 6 shows a positive but insignificant coefficient on *Post_Branch_Drop*, implying that small business lending in upper-income census tracts is unaffected by branch closings. Moreover, the coefficient on the interaction term is statistically insignificant. Together, the results show the low elasticity of credit supply to shocks (branch closings and developing mobile apps) in high-income census tracts. We speculate that this low elasticity comes from the early adoption of digital banking among the high-income population and is therefore less responsive to branch closings. Another possibility is that high-income borrowers may have more resources, such as relationships with banks, that allow them to access credit when needed.

In brief, branch closings affect most income-level census tracts, except for upper-income level areas. In addition, the cushion effect of having apps is evident only in relatively high-income areas. These results suggest that income disparity is associated with uneven accrual of benefits from mobile banking.

4.2.2 Mobile App Quality

Next, we evaluate the differential impact of app quality. The quality of an app is reflected in how efficiently the app can fulfill customers' needs. If app features are difficult for customers to grasp, it is less likely that mobile banking can perfectly substitute for in-person branches. In such a case, the marginal effect of having mobile apps after branch closings would be trivial. Therefore, we expect the effect to be stronger for highly satisfactory mobile apps and weaker among less satisfactory mobile apps.

We create a dummy variable *High_Quality* that equals one if the app quality score (described in Section 2.1) is above the median, otherwise it is zero. We interact *High_Quality* with $Post_Branch_Drop \times Have_App$ and regress small business lending in millions of dollars on

the triple interaction term. We report the results in Table 7.

The coefficient on $Post_Branch_Drop \times Have_App$ is positive and statistically insignificant. Coupled with the positive and statistically significant (at the 5% level) coefficient on the triple interaction term, the results imply that the cushion effect of having apps is prominent only when the apps are of high quality.

Overall, our results in this section provide evidence on the heterogeneity of the impact of banks' having mobile apps. We show that the effect is greater in relatively high-income areas. Moreover, the impact is likely affected by the efficiency of the app design, and only highly satisfactory apps have a significant impact on small business lending after branch closings.

4.3 Mechanism

To explain our results, we first examine whether the effect is mechanical by sampling bank-county observations that experience an increase in the number of branches. We then propose a mechanism based on the information advantage accumulated over years of service.

4.3.1 Asymmetric Effect

Our core evidence indicates that small business lending is less sensitive to branch closings when banks have mobile apps. A smaller reduction can result from the mobile app of attracting new customers or preserving existing customers. To test these two possibilities, we exploit bank-county observations with an increase in the number of branches. If the presence of mobile apps complements traditional bank branches, boosting overall lending activities, we expect to observe a positive and significant impact of having apps on small business lending in counties where banks expand their branch network.

We employ the same matching process detailed in Section 3.2, except that the treatment is replaced with bank-counties that experienced an increase in the number of branches. No significant differences are observed between the treatment and the control groups, as displayed in Panel A of Table 8. $Post_Branch_Increase$ is a new indicator that equals one after a bank increases the number of branches, otherwise it is zero. We interact $Have_App$ with $Post_Branch_Increase$ to capture the effect of having apps on small business lending after banks expand the branch network. The results are reported in Panel B of Table 8.

The coefficient on the interaction term is positive but statistically insignificant. This implies that having mobile apps may not contribute significantly to the growth of small business lending when banks expand their branch network. When considered alongside the results in Table 4, these findings provide some suggestive evidence supporting the notion that mobile banking plays a role in preserving existing borrowers when banks close branches, rather than attracting new customers. In other words, mobile banking appears to lack the capacity to function similarly to traditional branches in establishing new relationships.

4.3.2 Branch Service Year

We show that mobile banking relies on information and well-established relationships to help banks extend loans to existing customers without branches. Therefore, the effect of having apps should be more pronounced in situations with low information asymmetry and less pronounced in situations with high information asymmetry.

To test this idea, we calculate the average service year of a bank's closed branches in a county (*Mean_Service_Year*) as a proxy for information asymmetry between lenders and borrowers. The longer a branch has served the county, the more information is possessed by the lender. We interact *Mean_Service_Year* with *Post_Branch_Drop* $\times$ *Have_App* to capture the marginal effect of information asymmetry on small business lending after banks close branches. The dependent variable is the dollar amount of small business lending in millions. We use the matched sample and report the results in Table 9.

As indicated by the negative but statistically insignificant coefficient on *Mean_Service_Year*, small business lending does not differ across branches with varying years of service. The coefficient on *Post_Branch_Drop* $\times$ *Mean_Service_Year* is negative and statistically significant at the 5% level, indicating that small business lending declines more for branches that serve the community longer. One explanation is that the switching cost is greater for consumers in longer-term relationships with banks.

The triple interaction term is positive and statistically significant. Combined with the positive and insignificant interaction term of *Post_Branch_Drop* $\times$ *Have_App*, the results suggest that the effect of mobile banking is pronounced only when information asymmetry is low.

In brief, having mobile apps helps preserve existing customers when banks close branches.

The effect is significant only when closed branches serve the community relatively longer. These findings imply that while mobile banking plays a role in customer retention, it may not entirely substitute for traditional bank branches, especially in addressing information asymmetry.

5 Conclusion

Banks reduce small business lending in a county where banks close branches. However, the reduction is less for banks with mobile apps. We rule out the possibility that the results are driven by varying credit demand or the difference between banks with and without branch reduction prior to branch closing. Moreover, we do not find a significant effect of having mobile apps on small business lending when banks increase the number of branches in the area. We segregate borrowers by their census tract income levels and find that relatively high-income groups benefit more from mobile banking. We provide further evidence supporting the main results by showing that the effect of having mobile apps is stronger for high-rated apps and weaker for low-rated apps. Based on these results, we conclude that banks' having apps can alleviate the negative impact of branch closings on small business lending.

We also explore the mechanism of the effect. We propose a mechanism based on information accumulation over years of branch service. We use the median service year of closed branches in a county as a proxy for information asymmetry between borrowers and banks. We find that the cushion effect of having apps decreases with the level of information asymmetry. Specifically, the cushion impact on small business lending is relatively smaller for closed branches that had been present for a shorter duration than for closed branches that had existed for a long duration. The results imply that the branch banking system remains important in providing credit to the local community. Mobile banking preserves the borrower-bank relationship and serves as an alternative to brick-and-mortar branches when banks reduce their physical presence. However, mobile banking cannot establish new relationships like branches do.

The implications are twofold. First, geographic proximity is still an important factor affecting loan decisions for information-opaque borrowers. In other words, mobile banking can help preserve existing relationships by continually extending loans to current customers after branch closure. However, it cannot generate new information and thus reduce information asymmetry the way a shorter distance does. Second, the benefits of mobile banking are disproportionate

among populations with different incomes. For those better equipped technologically, the inconvenience of accessing financial services will be less than that for those with limited technology exposure. As the trend of branch closures continues due to technological advancements, enhancing technological accessibility for underserved populations becomes increasingly important for promoting financial inclusion.

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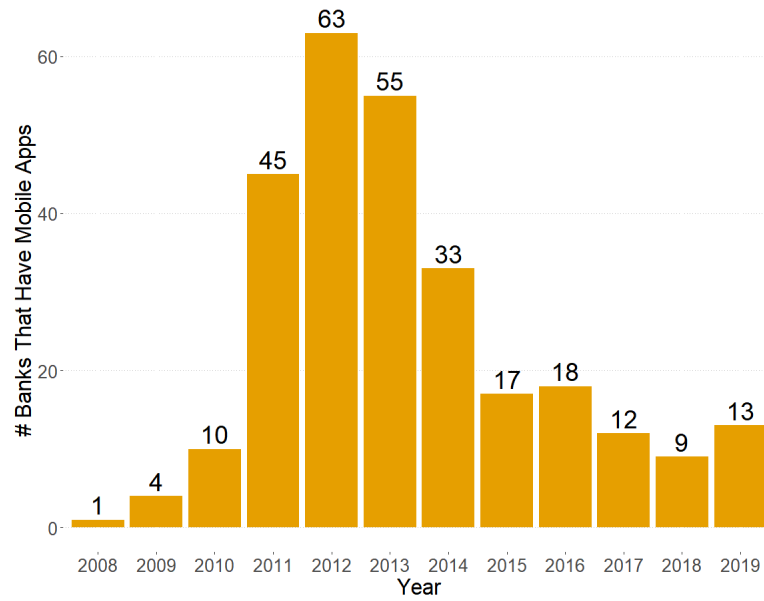
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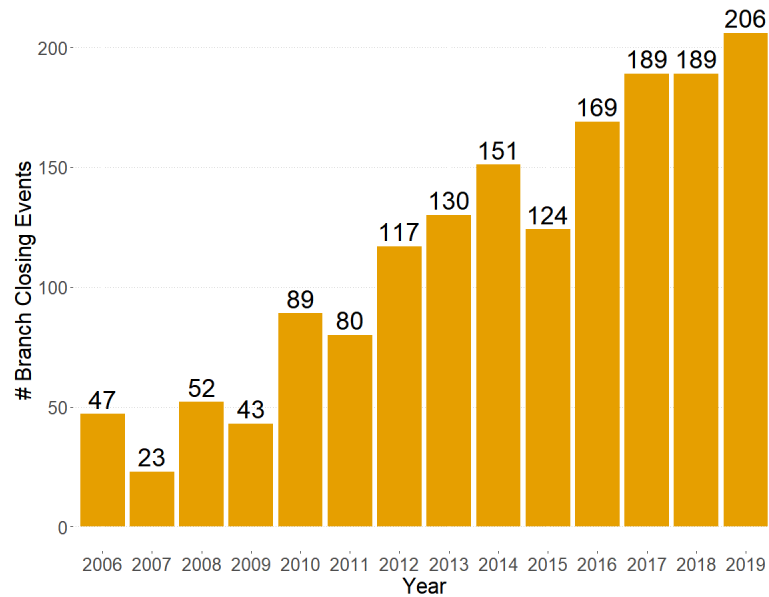
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Figure 1: Distribution of Bank Mobile Apps Release and Branch Closings



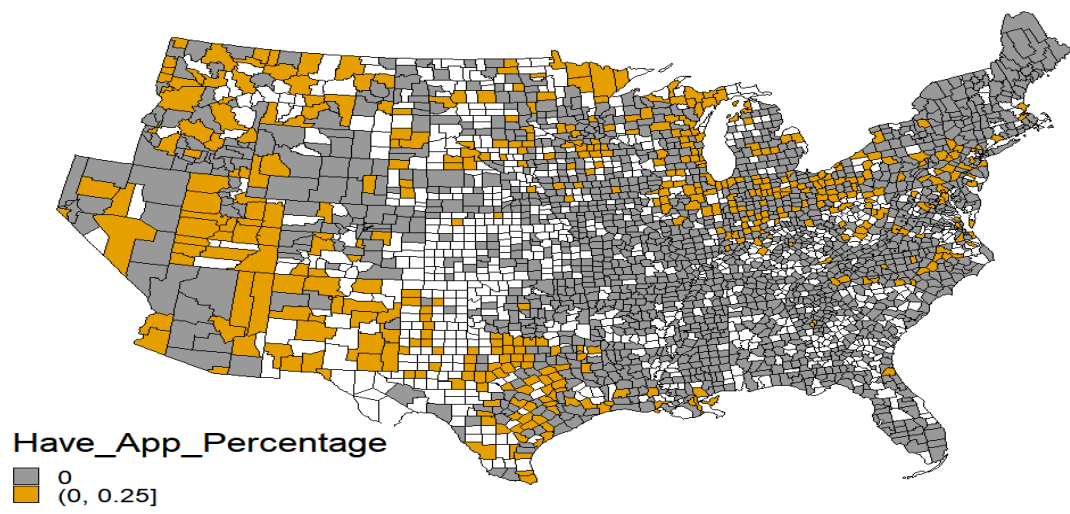
(a) Bank Apps Release



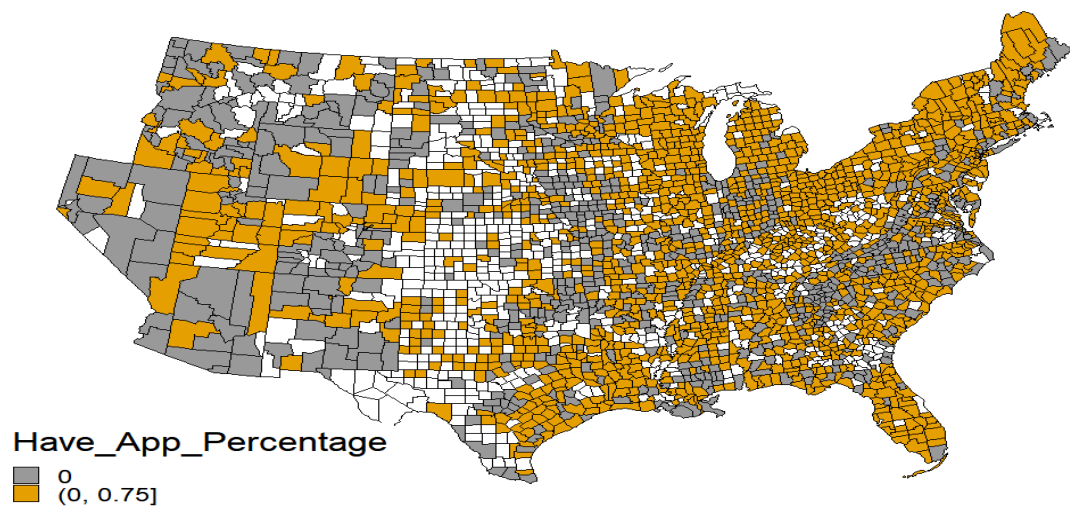
(b) Branch Closings

Figure 2: Geographic Distribution of Bank Branches Having Apps

2009



2014



2019

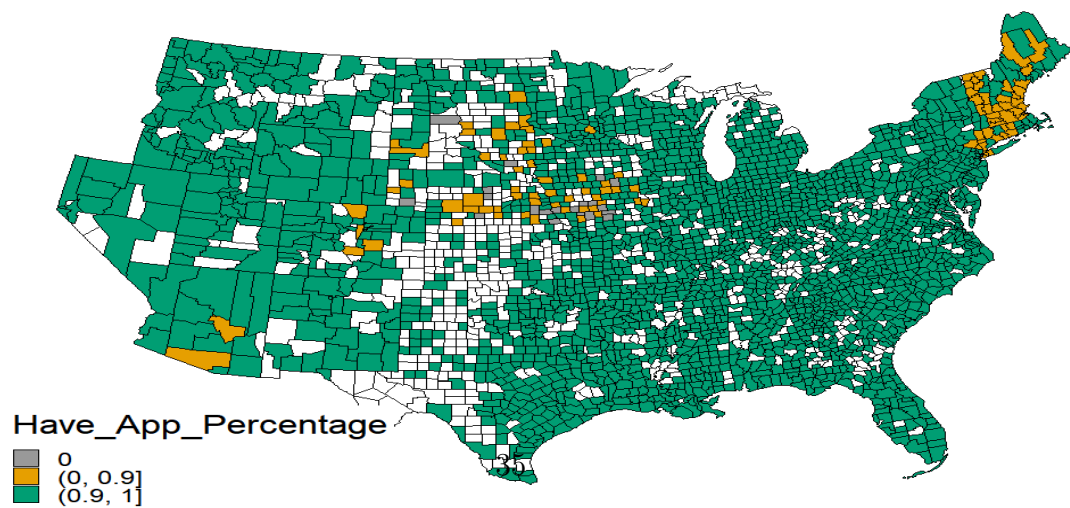
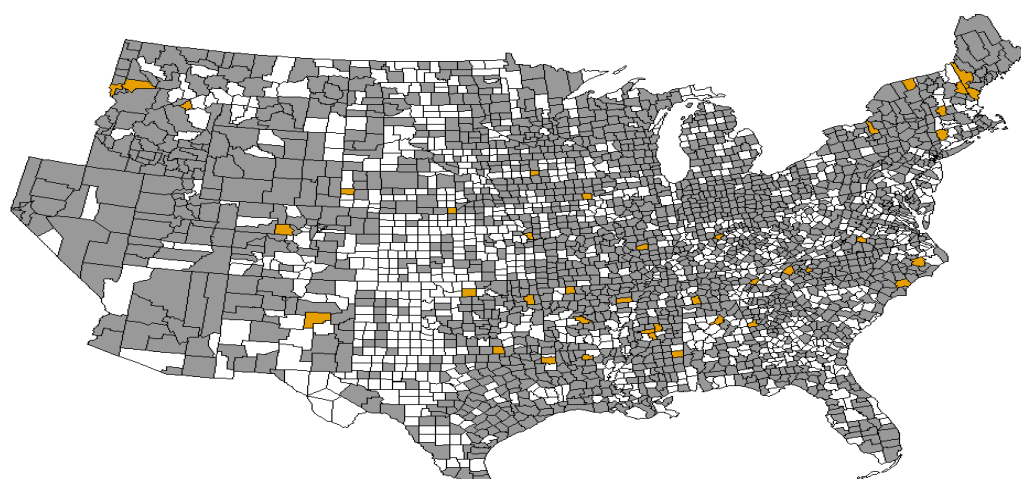


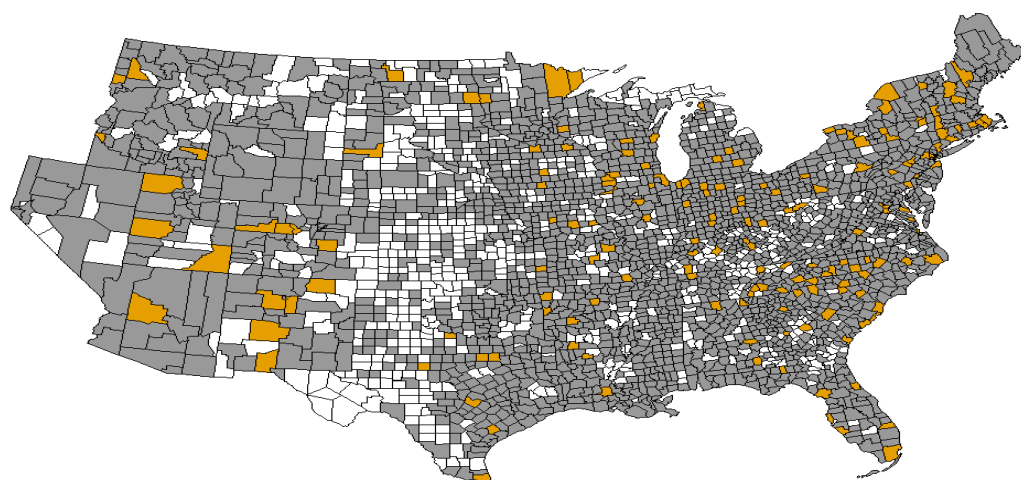
Figure 3: Geographic Distribution of Bank Branch Closings

2006



Have_Branch_Drop ■ 0 ■ 1

2019



Have_Branch_Drop ■ 0 ■ 1

Table 1: **Summary Statistics**

This table summarizes bank and county characteristics between 2005 and 2019. (*M*) means figures are in millions of US dollars. The variable definitions are in Appendix A.1.

	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Panel A: Bank Characteristics (Branch-Year Level and Bank-Year Level)							
# Unique Bank	282						
Have_App	84,299	0.652	0.476	0	1	1	1
Post_Branch_Drop	84,299	0.092	0.288	0	0	0	1
Deposit (M)	84,299	117.636	293.351	26.437	54.304	113.636	21,467.730
Branch	84,299	2.105	2.036	1	1	2	67
Share_Deposits	84,299	0.037	0.101	0.002	0.006	0.028	1.000
Share_Branch	84,299	0.037	0.092	0.002	0.008	0.033	1.000
Ln(Assets)	2,909	21.988	1.268	21.123	21.712	22.592	27.960
Loan/Assets	2,687	0.665	0.109	0.601	0.681	0.743	0.928
Equity/Assets	2,687	0.108	0.025	0.092	0.103	0.120	0.283
ROA	2,909	0.010	0.008	0.008	0.010	0.013	0.082
Ln(Wage)	3,152	17.995	1.539	16.954	17.604	18.577	24.075
Panel B: Small Business Lending (Branch-Year Level)							
SBL (\$, M)	84,299	5.011	9.523	0.548	2.071	5.477	280.931
SBL (\$) growth rate	75,256	8.814	200.317	-0.302	-0.004	0.354	3.667
Ln(SBL (\$))	84,299	13.537	3.820	13.214	14.544	15.516	19.454
SBL (#)	84,299	60.671	141.859	7	22	60	6,147
SBL_Low (\$, M)	84,299	0.213	1.056	0.000	0.000	0.000	45.294
SBL_Mod (\$, M)	84,299	0.884	2.526	0.000	0.042	0.811	113.395
SBL_Mid (\$, M)	84,299	2.426	4.449	0.200	1.042	2.841	173.524
SBL_Upp (\$, M)	84,299	1.416	3.476	0.000	0.089	1.319	125.555
Panel C: County Characteristics (County-Year Level)							
# Unique County	2578						
HPI (M)	26,183	0.167	0.110	0.102	0.139	0.196	1.784
Population (M)	32,430	0.130	0.352	0.020	0.040	0.100	10.095
Unemployment_Rate (%)	32,420	6.281	2.775	4.200	5.700	7.800	29.400
Tot_Deposit_County (M)	32,430	2,511.844	15,742.180	180.141	389.512	1,076.078	822,866.900
Tot_Branch_County	32,430	30.468	70.272	6	11	26	1,697
SBL_County (\$, M)	32,430	96.487	298.957	7.729	19.948	65.916	9,845.013
SBL_County (#)	32,430	2,844.240	10,169.910	250	588.5	1,706.8	354,890

Table 2: The Effects of Branch Closures and Bank Mobile App Release on SBL

This table reports the baseline results of estimating the impact of having mobile apps on small business lending after bank branch closings using Equation 2. The coefficient of interest is captured by the interaction term of $Post_Branch_Drop \times Have_App$. The dependent variable in Columns 1-3 is small business lending in millions of dollars, the growth rate of the dollar amount of small business lending, and the natural logarithm of small business lending in dollars. $Post_Branch_Drop$ is a dummy variable that takes the value of one during and after banks close branches in a county, otherwise it is zero. $Have_App$ is a dummy variable that takes the value of one during and after releasing mobile apps, and zero otherwise. In Panel A, we include bank- and bank-county level controls consisting of $Ln(Assets)$, $Loan/Assets$, $Equity/Assets$, ROA , $Ln(Wage)$, $Deposit_County(M)$, and $Branch_County$. Descriptions of these variables are in Appendix A.1. In all analyses in Panel A, We control for time-varying county-level variation and time-invariant bank variation by adding county-year and bank-fixed effects. In Panel B, we drop the bank controls to relieve the concern about “bad control variables” and add year-fixed effects. In Panel C, we exclude bank-counties that did not experience branch drop within the sample period to directly examine the impact of having apps on small business lending after branch closings. The model specifications for Columns 1-3 in Panel C are similar to those in Panel A, while Columns 4-6 align with the specifications outlined in Panel B. Standard errors are clustered at bank level and reported in parenthesis. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Panel A. Include Bank Controls

	<i>Dependent variable</i>		
	<i>SBL(\$)</i>	<i>SBL(\$)</i> growth rate	<i>Ln(SBL(\$))</i>
	(1)	(2)	(3)
Post_Branch_Drop	−0.728** (0.346)	−0.073*** (0.025)	−0.100* (0.058)
Have_App	0.021 (0.209)	−0.044 (0.323)	0.994 (1.053)
Post_Branch_Drop×Have_App	0.378** (0.182)	0.036* (0.020)	0.039* (0.022)
Bank Controls	✓	✓	✓
Bank FE	✓	✓	✓
County×Year FE	✓	✓	✓
Cluster Std Err		Bank	
Observations	38,776	33,814	38,786
Adjusted R ²	0.552	−0.142	0.720

Continue

Panel B. Exclude Bank Controls

	<i>Dependent variable</i>		
	<i>SBL(\$)</i>	<i>SBL(\$)</i> <i>growth rate</i>	<i>Ln(SBL(\$))</i>
	(1)	(2)	(3)
Post_Branch_Drop	−0.812** (0.414)	−0.032*** (0.009)	−0.163 (0.171)
Have_App	−0.445 (0.300)	0.053 (0.056)	0.088 (0.248)
Post_Branch_Drop × Have_App	0.416** (0.183)	0.015*** (0.002)	0.032* (0.014)
Bank FE	✓	✓	✓
Year FE	✓	✓	✓
County×Year FE	✓	✓	✓
Cluster Std Err		Bank	
Observations	84,299	75,256	84,299
Adjusted R ²	0.913	0.486	0.861

Panel C. Exclude No-Branch-Closing Bank-Counties

	<i>Dependent variable</i>					
	Include Bank Controls			Exclude Bank Controls		
	<i>SBL(\$)</i>	<i>SBL(\$)</i> <i>growth rate</i>	<i>Ln(SBL(\$))</i>	<i>SBL(\$)</i>	<i>SBL(\$)</i> <i>growth rate</i>	<i>Ln(SBL(\$))</i>
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Branch_Drop	−1.581** (0.641)	−0.065 (0.069)	−1.208*** (0.274)	−1.483** (0.589)	−0.056 (0.041)	−0.281** (0.130)
Have_App	1.113 (0.831)	0.044 (0.071)	0.372 (0.352)	0.405 (0.465)	0.004 (0.027)	0.030 (0.135)
Post_Branch_Drop×Have_App	0.634*** (0.196)	−0.035 (0.058)	0.944** (0.370)	0.413** (0.164)	−0.018 (0.019)	0.219* (0.114)
Bank Controls	✓	✓	✓			
Year FE				✓	✓	✓
Bank FE	✓	✓	✓	✓	✓	✓
County×Year FE	✓	✓	✓	✓	✓	✓
Cluster Std Err				Bank		
Observations	5,576	5,002	5,576	17,662	16,106	17,662
Adjusted R ²	0.832	0.306	0.649	0.505	−0.090	0.566

Table 3: Bank-County Matching Results ($K = 3$, Pairs = 145)

This table summarizes the difference in ex ante characteristics between the treatment bank-counties and control bank-counties before and after the matching process. For each branch closing event, we identify three closest neighbors (controls) among bank-counties that did not experience branch closures, determined by their logistic probability scores. From these three neighbors, we select one control bank-county that shares the same “*Have_App*” status in the branch closing year. A total of 145 pairs were matched. We alter the number of nearest neighbors (K) and report the matching results in Table A.3. The variable definitions can be found in Appendix A.1.

	Before		After	
	Difference in	P-Value	Difference in	P-Value
	Mean		Mean	
	(1)	(2)	(3)	(4)
Unemployment_Rate	0.296	0.000	0.024	0.937
Ln(HPI)	-0.028	0.044	-0.006	0.920
Ln(Population)	0.327	0.000	0.003	0.984
Ln(Tot_Deposit_County)	0.355	0.000	0.020	0.920
Ln(Tot_Branch_County)	0.335	0.000	0.030	0.840
Ln(SBL_County (\$))	0.340	0.000	0.039	0.842
Ln(SBL_County (#))	0.278	0.000	0.012	0.951
Share_Deposit	0.003	0.236	0.006	0.565
Share_Branch	0.006	0.013	0.007	0.478

Table 4: Baseline Regression Using The Matched Sample

This table reports the baseline results of estimating the differential effect of having apps on small business lending of the treatment versus the control bank-counties after bank branch closings. The model specifications are described in Equation 3. Standard errors are clustered at bank level and reported in parenthesis. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

	<i>Dependent variable</i>		
	<i>SBL(\$)</i>	<i>SBL(\$)</i> growth rate	<i>Ln(SBL(\$))</i>
	(1)	(2)	(3)
Post_Branch_Drop	−0.340*** (0.114)	−0.932** (0.389)	−0.053** (0.021)
Have_App	−0.073 (0.695)	11.384 (7.555)	−0.077 (0.154)
Post_Branch_Drop× Have_App	0.064** (0.032)	1.065* (0.632)	0.008* (0.004)
Event×Bank FE	✓	✓	✓
Event-Time FE	✓	✓	✓
Cluster Std Err		Bank	
Observations	2,899	2,610	2,899
Adjusted R ²	0.839	0.069	0.791

Table 5: The Impact of Having Apps on SBL Dynamics around Branch Closures

This table examines the parallel trend assumption of small business lending between two groups of treatment and control bank-counties around branch closing events. The first group comprises treatment and control bank-counties without mobile apps during the year of branch closures, while the second group consists of treatment and control bank-counties with mobile apps when experiencing branch closures. Our focal point is the year preceding each branch closing event, with a dynamic window spanning 4 years before and 1 year after each branch closing. *Treatment* is an indicator variable that takes the value of one for bank-counties experienced branch closings. Details about the matching process is documented in Section 3.2. We include the event-bank and event-time fixed effects. Standard errors are clustered at bank level and reported in parenthesis. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

	<i>Dependent variable: SBL (\$) in millions</i>
	(1)
Event_Time (-4) $\times$ Treatment $\times$ Have_App	-0.794 (0.945)
Event_Time (-3) $\times$ Treatment $\times$ Have_App	-0.321 (0.842)
Event_Time (-2) $\times$ Treatment $\times$ Have_App	-0.302 (1.102)
Event_Time (0) $\times$ Treatment $\times$ Have_App	0.894*** (0.295)
Event_Time (1) $\times$ Treatment $\times$ Have_App	0.689 (0.632)
Event_Time (-4) $\times$ Treatment	0.891 (1.043)
Event_Time (-3) $\times$ Treatment	0.351 (0.755)
Event_Time (-2) $\times$ Treatment	-0.503 (0.918)
Event_Time (0) $\times$ Treatment	-1.673** (0.636)
Event_Time (1) $\times$ Treatment	-0.965 (1.223)
Event $\times$ Bank FE	✓
Event-Time FE	✓
Cluster Std Err	Bank
Observations	2,899
Adjusted R ²	0.837

Table 6: Heterogeneity: Census Tracts' Income Level

This table reports the results of cross-sectional analysis by borrowers' census tract of residence income level. The dependent variable in Columns 1-4 is small business lending in millions of US dollars in low, moderate, middle, and upper-income census tracts aggregated at the county level. The Census Bureau determines a census tract's income level by comparing the median household income in the census tract to the proportion of median household income in metropolitan statistical areas. We include event-bank and event-time fixed effects. Standard errors are clustered at bank level and are reported in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

	<i>Dependent variable: SBL (\$) in millions</i>			
	Low (1)	Moderate (2)	Middle (3)	Upper (4)
Post_Branch_Drop	-0.005** (0.002)	-0.065** (0.026)	-0.280*** (0.075)	0.098 (0.072)
Have_App	0.052 (0.077)	0.514*** (0.170)	0.109 (0.335)	0.146 (0.206)
Post_Branch_Drop× Have_App	-0.015 (0.012)	0.014 (0.022)	0.168*** (0.057)	0.015 (0.031)
Event×Bank FE	✓	✓	✓	✓
Event-Time FE	✓	✓	✓	✓
Cluster Std Err			Bank	
Observations	2,899	2,899	2,899	2,899
Adjusted R ²	0.653	0.770	0.762	0.753

Table 7: Heterogeneity: Mobile App Quality

This table reports the results of cross-sectional analysis by mobile app quality. The dependent variable is small business lending in millions of US dollars. *High_Quality* is a dummy variable that is one for banks whose mobile app quality score is above the median, otherwise it is zero. The app quality score is estimated by computing Equation 1. We include event-bank and event-time fixed effects. Standard errors are clustered at bank level and are reported in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

	<i>Dependent variable: SBL (\$) in millions</i>
	(1)
Post_Branch_Drop	-1.874* (1.123)
Have_App	1.224 (1.302)
Post_Branch_Drop $\times$ Have_App	1.097 (1.190)
Post_Branch_Drop $\times$ High_Quality	1.329 (1.133)
Have_App $\times$ High_Quality	0.064 (1.628)
Post_Branch_Drop $\times$ Have_App $\times$ High_Quality	0.673** (0.283)
Event $\times$ Bank FE	✓
Event-Time FE	✓
Cluster Std Err	Bank
Observations	2,899
Adjusted R ²	0.840

Table 8: Asymmetric Effect

This table examines the differential impact of having apps on small business lending for bank-counties that experienced an increase in the number of branches. Employing the identical matching procedure detailed in Section 3.2, we designate the branch-increase event as the treatment. Panel A documents the difference between the treatment and control groups across nine dimensions. Panel B presents the result using the matched sample. The dummy variable *Post_Branch_Increase* assumes a value of one during and after a bank increases the number of branches in a county, and zero otherwise. The regression incorporates event-bank and event-time fixed effects. Standard errors are clustered at bank level and are reported in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Panel A. Summary Statistics after Matching

	K=3 (53 pairs)	
	Difference in Mean	P-Value
	(1)	(2)
Unemployment_Rate	-0.130	0.753
Ln(HPI)	0.035	0.716
Ln(Population)	0.198	0.386
Ln(Tot_Deposit_County)	0.220	0.488
Ln(Tot_Branch_County)	0.188	0.398
Ln(SBL_County (\$))	0.232	0.362
Ln(SBL_County (#))	0.216	0.383
Share_Deposit	0.049	0.051
Share_Branch	0.034	0.120

Panel B. Matched Sample Regression

	<i>Dependent variable: SBL (\$)</i>
	(1)
Post_Branch_Increase	0.711 (2.990)
Have_App	-1.301 (0.896)
Post_Branch_Increase×Have_App	0.902 (2.403)
Event×Bank FE	✓
Event-Time FE	✓
Cluster Std Err	Bank
Observations	1,040
Adjusted R ²	0.865

Table 9: Mechanism: Information Asymmetry

This table reports the results of the proposed mechanism of information asymmetry. We argue that low information asymmetry between branches and borrowers enables banks to continue extending loans to existing customers after branch closings. We use the number of years the closed branches had served the community as a proxy for information asymmetry. Standard errors are clustered at bank level and are reported in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

	<i>Dependent variable: SBL (\$) in millions</i>
	(1)
Post_Branch_Drop	-0.345*** (0.115)
Have_App	-0.069 (0.700)
Mean_Service_Year	-0.007 (0.008)
Post_Branch_Drop×Have_App	0.061 (0.100)
Post_Branch_Drop× Mean_Service_Year	-0.004** (0.002)
Have_App× Mean_Service_Year	0.014 (0.010)
Post_Branch_Drop× Have_App× Mean_Service_Year	0.004** (0.002)
Event×Bank FE	✓
Event-Time FE	✓
Cluster Std Err	Bank
Observations	2,899
Adjusted R ²	0.839

Appendix

Figure F.1: App Reviews - Pacific Western Bank

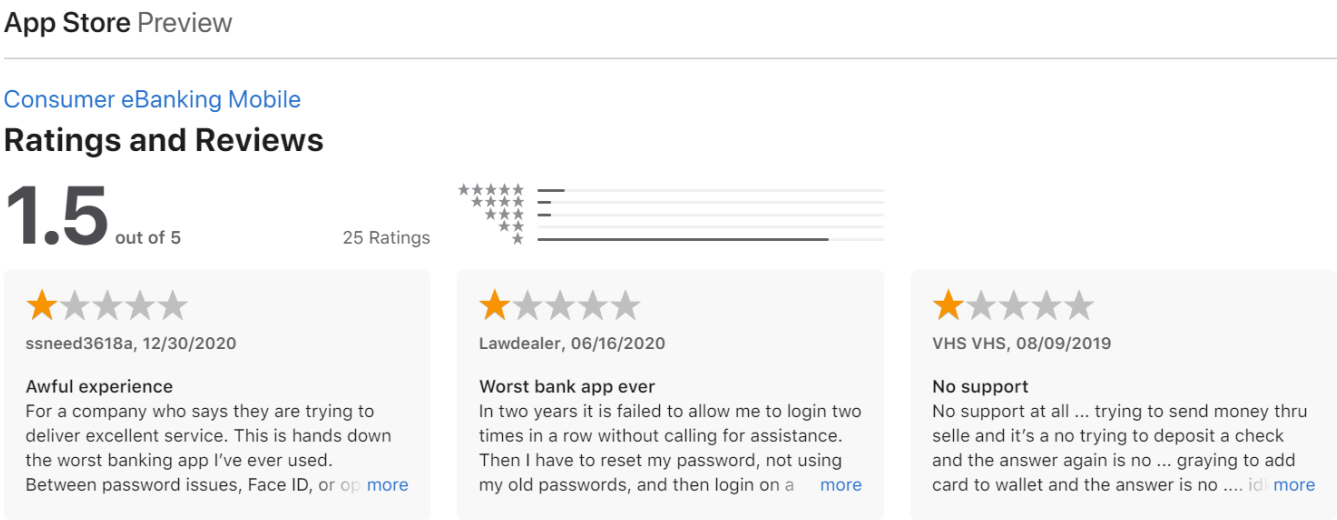


Figure F.2: Branch Closing Sample Selection

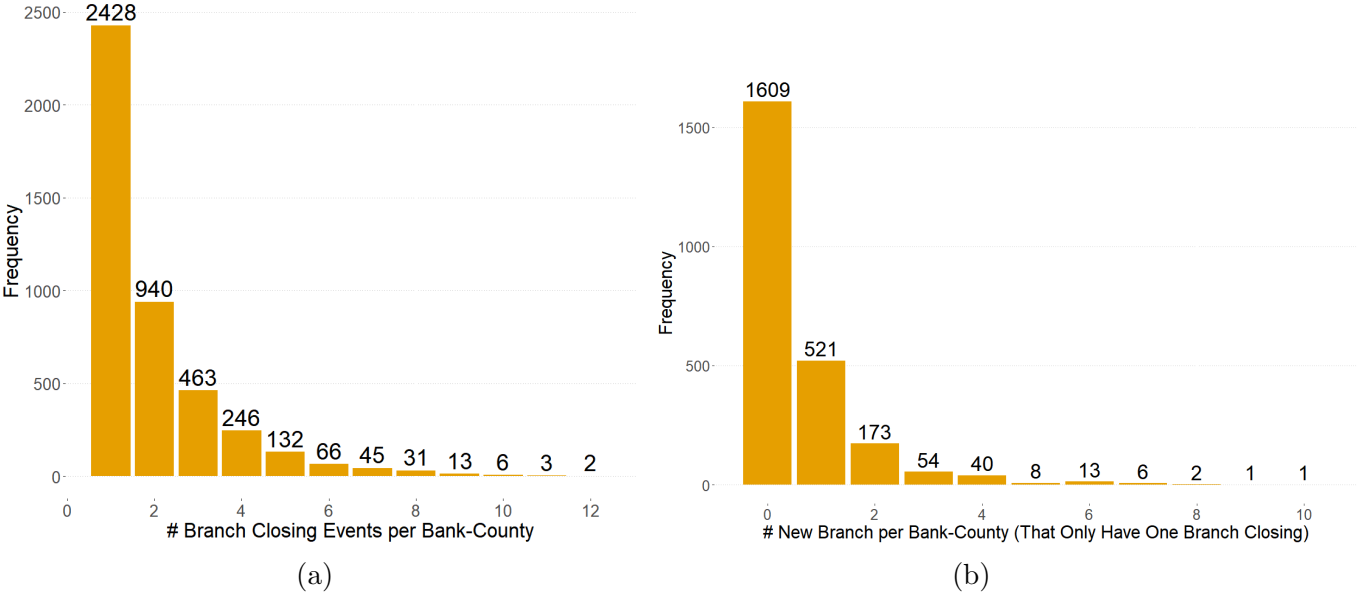


Table A.1: **Variable Definitions**

Variables	Definition
Have_App	A dummy variable that is one during and after banks having mobile apps, and zero otherwise.
Post_Branch_Drop	A dummy variable that is one for years during and after branch closings, and zero otherwise.
SBL (\$)	The dollar amount of small business lending at the bank-county level
SBL (\$) growth rate	$\frac{SBL(\$)_t - SBL(\$)_{t-1}}{SBL(\$)_{t-1}}$
Ln(SBL (\$))	The natural logarithm of small business lending in dollars
SBL (#)	The number of small business lending originations at the bank-county level
SBL_Low (\$)	The dollar amount of small business lending in low-income census tract aggregated at the county level.
SBL_Moderate (\$)	The dollar amount of small business lending in moderate-income census tract aggregated at the county level.
SBL_Middle (\$)	The dollar amount of small business lending in middle-income census tract aggregated at the county level.
SBL_Upper (\$)	The dollar amount of small business lending in upper-income census tract aggregated at the county level.
Ln(Assets)	The natural logarithm of total assets in US dollars
Loan/Assets	The ratio of total loans over total assets
Equity/Assets	The ratio of total equity over total assets
ROA	The ratio of net income over total assets
Ln(Wage)	The natural logarithm of salaries and wages in US dollars
Deposits	A bank's deposits in a county
Branch	A bank's number of full-service branches in a county
Share_Deposit	The proportion of a bank's deposits in a county to its total deposits
Share_Branch	The proportion of a bank's number of branches in a county to its total number of branches

Continue

Variables	Definition
HPI	The median housing price in a county
Tot_Deposit_County	The sum of deposits across all FDIC-insured branches in a county
Tot_Branch_County	The total number of FDIC-insured branches in a county
SBL_County (\$)	The dollar amount of small business lending across all banks in a county
SBL_County (#)	The number of small business loan origination across all banks in a county
Avg_mobile_cov	A bank's average exposure to mobile wireless coverage across counties where a bank operates, weighted by the share of deposits in a county relative to a bank's total deposits in a given year
Ln(Avg_distance+1)	The natural logarithm of one plus the Haversine distance between a bank's branches and their centroid within a county is calculated. The bank-county centroid is determined as the average longitude and latitude of the bank's branches within that county

Table A.2: **Banks with the Highest and the Lowest App Quality Scores**

The table lists the number of branches in 2005 and 2019 for two groups: the top 10 banks with the highest app quality scores and the bottom 10 banks with the lowest app quality scores. In our sample, the bank branches considered are non-headquarters offices that operate during standard business hours and offer comprehensive services in 48 contiguous U.S. states. Our app quality measure does not favor banks with more branches or large asset sizes, as three out of the four largest banks, based on branch quantity and total assets, do not feature in our top 10 list. The missing values in the number of branches in 2005 can be attributed to subsequent branch establishments for First Republic Bank and Servisfirst Bank, alterations in RSSD ID for Cadence Bank, and shifts in institution class for Berkshire Bank.

10 Banks with the Highest App Quality Scores

Bank	Tech	#Branches in 2005	#Branches in 2019
International Bank of Commerce	15.30	157	113
Independent Bank	14.11	11	93
Silicon Valley Bank	13.42	4	4
Arvest Bank	13.05	192	264
Capital One	12.84	273	472
Plainscapital Bank	12.01	21	60
First Republic Bank	11.90		77
JPMorgan Chase Bank	10.96	2379	4929
Bell Bank	10.89	10	21
United Community Bank	10.66	49	138

10 Banks with the Lowest App Quality Scores

Bank	Tech	#Branches in 2005	#Branches in 2019
Washington Trust Bank	0.40	33	40
Signature Bank	-0.06	12	30
Cadence Bank	-0.21		96
Berkshire Bank	-0.37		132
Glacier Bank	-0.58	10	143
Pacific Western Bank	-2.33	21	74
Eagle Bank	-2.86	7	19
Mechanics Bank	-2.90	27	44
Popular Bank	-2.90	137	50
Servisfirst Bank	-2.90		19

Table A.3: Matching with Different K Nearest Neighbors

This table presents the matching results with varying number of nearest neighbors ($K = 2$ and 4) and the corresponding baseline results using different matched samples. Standard errors are clustered at bank level and reported in parenthesis. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Panel A. Summary Statistics after Matching

	K = 2 (59 pairs)		K = 4 (232 pairs)	
	Difference	P-Value	Difference	P-Value
	(1)	(2)	(3)	(4)
Unemployment_Rate	0.158	0.737	0.054	0.804
Ln(HPI)	0.011	0.911	-0.012	0.812
Ln(Population)	-0.021	0.939	-0.025	0.843
Ln(Tot_Deposit_County)	0.043	0.899	0.011	0.219
Ln(Tot_Branch_County)	0.027	0.911	-0.009	0.936
Ln(SBL_County (\$))	0.021	0.948	-0.006	0.969
Ln(SBL_County (#))	0.001	0.999	-0.032	0.826
Share_Branch	-0.015	0.426	0.008	0.375
Share_Deposit	-0.020	0.301	0.011	0.219

Panel B. Baseline Regression Using Different Matched Samples

	<i>Dependent variable</i>		
	<i>SBL(\$)</i>	<i>SBL(\$)</i> growth rate	<i>Ln(SBL(\$))</i>
	(1)	(2)	(3)
Panel B1. Baseline Regression with K = 2			
Post_Branch_Drop	-0.680*** (0.225)	-0.465* (0.280)	-0.056** (0.022)
Have_App	0.657 (1.031)	-0.551 (6.230)	0.016 (0.216)
Post_Branch_Drop× Have_App	0.347** (0.147)	0.680 (1.122)	0.002* (0.001)
Observations	1,210	1,092	1,210
Adjusted R ²	0.580	0.011	0.740
Panel B2. Baseline Regression with K = 4			
Post_Branch_Drop	-0.416*** (0.112)	0.030 (0.593)	-0.054*** (0.016)
Have_App	0.453 (0.476)	2.990 (3.778)	-0.066 (0.129)
Post_Branch_Drop× Have_App	0.212*** (0.067)	0.270 (0.423)	0.021** (0.010)
Observations	4,676	4,217	4,676
Adjusted R ²	0.525	0.033	0.812

Table A.4: Instrumental Variable Analysis

This table presents the results of applying the instrumental variable strategy to examine the relationship between banks' having apps and small business lending following bank branch closures. The variable *avg_mobile_cov*, an instrument for *having app*, is computed by estimating Equation 5. The instrument captures the average exposure to mobile wireless coverage across counties where a bank operates, weighted by the share of deposits in a county relative to a bank's total deposits in a given year. As the county level mobile wireless coverage data are sourced from two sources, we provide separate summary statistics in Panel A. The variable $\ln(\text{avg_distance}+1)$, an instrument for *Post_Branch_Drop*, is calculated as the natural logarithm of the average distance between a bank's branches and it's centroid within a county plus one. It serves as a measure of the geographical dispersion of a bank's branches within a county. Panel B reports the results of two-stage least squares regression. We include a set of controls and fixed effects similar to Equation 2. We report the F stats for both IVs in the table. Standard errors are clustered at bank level for robustness. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel A. Summary Statistics

Statistic	N	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)	Max
IV for <i>Have_App</i>							
<u>2010-2014 (National Telecommunications & Information Association)</u>							
<i>mobile_cov</i> (%)	45,987	93.648	7.394	92.352	95.885	97.761	100.000
<i>avg_mobile_cov</i> (%)	1,342	95.008	4.081	93.874	96.029	97.496	99.878
<u>2015-2019 (Federal Communications Commission)</u>							
<i>mobile_cov</i> (%)	52,289	99.525	1.811	99.936	100.000	100.000	100.000
<i>avg_mobile_cov</i> (%)	1,413	99.743	0.649	99.858	99.974	99.996	100.000
<u>2010-2019</u>							
<i>avg_mobile_cov</i> (%)	2,755	97.437	3.732	96.079	98.814	99.977	100.000
IV for <i>Post_Branch_Drop</i>							
$\ln(\text{avg_distance}+1)$	73,255	3.862	4.371	0.000	0.000	8.786	15.285

Panel B. 2SLS Regression

	<i>Dependent variable</i>				
	1st Stage		2rd Stage		
	Have_App	Post_Branch_Drop	<i>SBL(\$)</i>	<i>SBL(\$)</i> growth rate	<i>Ln(SBL(\$))</i>
	(1)	(2)	(3)	(4)	(5)
<i>avg_mobile_cov</i>	0.006*** (0.002)				
<i>ln(avg_distance+1)</i>		−0.001** (0.000)			
<i>Post_Branch_Drop</i>			−1.053** (0.490)	−0.036 (0.029)	−0.154*** (0.014)
<i>Have_App</i>			0.869 (0.798)	0.183 (0.373)	−5.064 (4.627)
<i>Post_Branch_Drop</i> × <i>Have_App</i>			0.374*** (0.060)	0.003* (0.002)	0.114*** (0.038)
Bank Controls	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓
County-Year FE	✓	✓	✓	✓	✓
Cluster Std Err			Bank		
Observations	27,262	27,262	27,262	24,783	27,262
Adjusted R ²	0.660	0.050	0.539	−0.026	0.713
F Stat	67.81***	24.15***			

Online Appendix

Table OA.1: The Effects of Branch Closures and Bank Mobile App Release on SBL (with Constant *Have_App*)

This table examines the robustness of Table 2 full-sample regression to keeping the variable *Have_App* constant. We replicate the analysis in Panel C of Table 2, with the modification that *Have_App* is treated as a constant variable. It is one if branches have an app before closures, and zero otherwise. Standard errors are clustered at bank level and reported in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	<i>Dependent variable</i>					
	Include Bank Controls			Exclude Bank Controls		
	<i>SBL</i> ($\$$)	<i>SBL</i> ($\$$) <i>growth rate</i>	<i>Ln</i> (<i>SBL</i> ($\$$))	<i>SBL</i> ($\$$)	<i>SBL</i> ($\$$) <i>growth rate</i>	<i>Ln</i> (<i>SBL</i> ($\$$))
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Branch_Drop	−1.512*** (0.259)	−0.095 (0.063)	−2.808*** (0.482)	1.541** (0.602)	−0.018 (0.030)	−0.372*** (0.125)
Have_App	0.052 (0.842)	0.025 (0.057)	0.410 (0.314)	0.891 (0.803)	0.034 (0.024)	0.037 (0.075)
Post_Branch_Drop × Have_App	0.507*** (0.159)	−0.028 (0.054)	0.736** (0.330)	0.630** (0.245)	−0.027 (0.020)	0.263* (0.134)
Bank Controls	✓	✓	✓			
Year FE				✓	✓	✓
Bank FE	✓	✓	✓	✓	✓	✓
County×Year FE	✓	✓	✓	✓	✓	✓
Cluster Std Err				Bank		
Observations	5,576	5,002	5,576	17,662	16,106	17,662
Adjusted R ²	0.873	0.307	0.659	0.505	−0.090	0.567

Table OA.2: Baseline Regression Using The Matched Sample (with Constant *Have_App*)

This table examines the robustness of Table 4 difference-in-differences regression to keeping the variable *Have_App* constant. *Have_App* is defined as a bank-county level time-invariant variable in this analysis. This variable takes a value of one if the treatment bank-counties have apps during branch closures and zero if they do not. The control group uses the treatment branch closing year as a reference point for determining *Have_App*. Both treatment and control groups share the same *Have_App* value, as this is an essential step in the matching process. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

	<i>Dependent variable</i>		
	<i>SBL</i> ($\$$)	<i>SBL</i> ($\$$) <i>growth rate</i>	<i>Ln</i> (<i>SBL</i> ($\$$))
	(1)	(2)	(3)
Post_Branch_Drop	-0.326*** (0.109)	-0.998** (0.415)	-0.039** (0.015)
Post_Branch_Drop $\times$ Have_App	0.136** (0.059)	1.419* (0.842)	0.007* (0.004)
Event $\times$ Bank FE	✓	✓	✓
Event-Time FE	✓	✓	✓
Cluster Std Err		Bank	
Observations	2,899	2,610	2,899
Adjusted R ²	0.839	0.064	0.790

Table OA.3: The Impact of Having Apps on SBL Dynamics around Branch Closures (with Constant *Have_App*)

This table examines the robustness of Table 5 dynamic regression of small business lending on branch closures and mobile app adoption to keeping the variable *Have_App* constant. *Have_App* is defined as a bank-county level time-invariant variable in this analysis. This variable takes a value of one if the treatment bank-counties have apps during branch closures and zero if they do not. The control group uses the treatment branch closing year as a reference point for determining *Have_App*. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	<i>Dependent variable: SBL (\$) in millions</i>
	(1)
Event_Time (-4) $\times$ Treatment $\times$ Have_App	-0.638 (1.116)
Event_Time (-3) $\times$ Treatment $\times$ Have_App	-0.051 (1.572)
Event_Time (-2) $\times$ Treatment $\times$ Have_App	-0.115 (1.360)
Event_Time (0) $\times$ Treatment $\times$ Have_App	1.259*** (0.416)
Event_Time (1) $\times$ Treatment $\times$ Have_App	0.739 (0.862)
Event_Time (-4) $\times$ Treatment	0.860 (1.340)
Event_Time (-3) $\times$ Treatment	-0.407 (1.705)
Event_Time (-2) $\times$ Treatment	-0.694 (1.514)
Event_Time (0) $\times$ Treatment	-3.147** (1.385)
Event_Time (1) $\times$ Treatment	-0.365 (0.823)
Event $\times$ Bank FE	✓
Event-Time FE	✓
Cluster Std Err	Bank
Observations	2,899
Adjusted R ²	0.845

Table OA.4: Heterogeneity: Census Tracts' Income Level (with Constant *Have_App*)

This table examines the robustness of Table 6 difference-in-differences regression by borrowers' income levels to keeping the variable *Have_App* constant. *Have_App* is defined as a bank-county level time-invariant variable in this analysis. This variable takes a value of one if the treatment bank-counties have apps during branch closures and zero if they do not. The control group uses the treatment branch closing year as a reference point for determining *Have_App*. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	<i>Dependent variable: SBL (\$) in millions</i>			
	Low (1)	Moderate (2)	Middle (3)	Upper (4)
Post_Branch_Drop	-0.061* (0.032)	-0.171** (0.068)	-0.428*** (0.114)	0.456 (0.423)
Post_Branch_Drop × Have_App	-0.032 (0.260)	0.189 (0.300)	0.472*** (0.157)	0.174 (0.472)
Event × Bank FE	✓	✓	✓	✓
Event-Time FE	✓	✓	✓	✓
Cluster Std Err			Bank	
Observations	2,899	2,899	2,899	2,899
Adjusted R ²	0.654	0.769	0.761	0.753

Table OA.5: Heterogeneity: Mobile App Quality (with Constant *Have_App*)

This table examines the robustness of Table 7 difference-in-differences regression by app quality to keeping the variable *Have_App* constant. *Have_App* is defined as a bank-county level time-invariant variable in this analysis. This variable takes a value of one if the treatment bank-counties have apps during branch closures and zero if they do not. The control group uses the treatment branch closing year as a reference point for determining *Have_App*. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	<i>Dependent variable: SBL (\$) in millions</i>
	(1)
Post_Branch_Drop	-1.428** (0.613)
Post_Branch_Drop×Have_App	0.538* (0.299)
Post_Branch_Drop×High_Quality	-0.011 (0.206)
Post_Branch_Drop×Have_App× High_Quality	0.684* (0.385)
Event × Bank	✓
Event-Time FE	✓
Cluster Std Err	Bank
Observations	2,899
Adjusted R ²	0.839

Table OA.6: Asymmetric Effect (with Constant *Have_App*)

This table examines the robustness of Table 8 difference-in-differences regression of small business lending on branch expansions and mobile app adoption to keeping the variable *Have_App* constant. *Have_App* is defined as a bank-county level time-invariant variable in this analysis. This variable takes a value of one if the treatment bank-counties have apps during branch closures and zero if they do not. The control group uses the treatment branch closing year as a reference point for determining *Have_App*. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	<i>Dependent variable: SBL (\$)</i>
	(1)
Post_Branch_Increase	1.134 (1.953)
Post_Branch_Increase×Have_App	1.107 (2.074)
Event×Bank FE	✓
Event-Time FE	✓
Cluster Std Err	Bank
Observations	1,040
Adjusted R ²	0.819

Table OA.7: Mechanism: Information Asymmetry (with Constant *Have_App*)

This table examines the robustness of Table 9 difference-in-differences regression by closed branches' service year to keeping the variable *Have_App* constant. *Have_App* is defined as a bank-county level time-invariant variable in this analysis. This variable takes a value of one if the treatment bank-counties have apps during branch closures and zero if they do not. The control group uses the treatment branch closing year as a reference point for determining *Have_App*. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	<i>Dependent variable: SBL (\$) in millions</i>
	(1)
Mean_Service_Year	0.066** (0.031)
Post_Branch_Drop×Have_App	0.323 (1.129)
Post_Branch_Drop× Mean_Service_Year	0.069 (0.115)
Have_App× Mean_Service_Year	−0.088 (0.113)
Post_Branch_Drop× Have_App× Mean_Service_Year	0.085*** (0.028)
Event×Bank FE	✓
Event-Time FE	✓
Cluster Std Err	Bank
Observations	2,899
Adjusted R ²	0.828

Table OA.8: Baseline Regression Using Different Matched Samples (with Constant *Have_App*)

This table examines the robustness of Table A.3 difference-in-differences regression using different matched samples to keeping the variable *Have_App* constant. *Have_App* is defined as a bank-county level time-invariant variable in this analysis. This variable takes a value of one if the treatment bank-counties have apps during branch closures and zero if they do not. The control group uses the treatment branch closing year as a reference point for determining *Have_App*. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	<i>Dependent variable</i>		
	<i>SBL(\$)</i> (1)	<i>SBL(\$)</i> <i>growth rate</i> (2)	<i>Ln(SBL(\$))</i> (3)
Baseline Regression with K = 2			
Post_Branch_Drop	-1.132** (0.472)	-0.722 (0.697)	-0.063** (0.024)
Post_Branch_Drop × Have_App	0.394** (0.187)	0.625 (0.991)	0.002* (0.001)
Observations	1,210	1,092	1,210
Adjusted R ²	0.594	0.001	0.630
Baseline Regression with K = 4			
Post_Branch_Drop	-0.597*** (0.171)	-0.001 (0.219)	-0.059*** (0.014)
Post_Branch_Drop × Have_App	0.206*** (0.065)	0.046 (0.127)	0.016** (0.008)
Event × Bank FE	✓	✓	✓
Event-Time FE	✓	✓	✓
Cluster Std Err		Bank	
Observations	4,676	4,217	4,676
Adjusted R ²	0.459	0.002	0.643