Keeping Up in the Digital Era:

How Mobile Technology Is Reshaping the Banking Sector*

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Abstract

I show that the growing trend in financial services digitalization has introduced a novel dimension along which commercial banks compete. Based on the analysis of newly hand-collected data on the launch date of banks' smartphone apps, I show that small community banks (SCBs) have been slow to provide mobile banking services to their customers. As a consequence, when the local mobile infrastructure improves–a positive shock to smartphone apps' usage and value–they lose deposits to larger, better-digitalized banks. Further, this dynamic negatively affects their small business lending, for these institutions have historically relied on information and liquidity synergies with deposits to maintain their competitive advantage in such markets. Larger banks and FinTech firms prove to be imperfect substitutes in this setting, and the local economy benefits less from digitalization in areas where SCBs had an important presence before its advent.

Keywords: Digitalization, Mobile Technology, FinTech, Banking, Depository Institutions, Commercial Banks, Small Business Lending

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1 Introduction

Recent literature has emphasized the rise of financial services digitalization by tracking the growing competition posed by FinTech firms *to* traditional commercial banks (e.g., Buchak et al. (2018), Gopal and Schnabl (2020), Erel and Liebersohn (2020), Berg et al. (2021)). In this paper, I investigate the changes that financial services digitalization has triggered *within* the traditional commercial banking sector.

I show small community banks in the U.S. are slow to adopt mobile technology. Therefore, they lose deposits to better-digitalized banks following mobile infrastructure improvements. Further, they increase branch closures and exploit their remaining customers by keeping deposit rates low. Additionally, deposit outflows cause them to decrease small business lending. I show neither larger banks nor FinTech firms fully substitute for this decline. I conclude by discussing the negative consequences of these dynamics for small businesses and the local economy.

To the best of my knowledge, this paper is the first to directly measure the impact of mobile technology adoption on traditional banking. It does so with the introduction of two new datasets. The first covers the existence of mobile banking services for the consumer. For each U.S. depository institution, I manually collect information on the date it launched its first consumer banking application on either the Apple Store or Google Play. The second captures the value of these applications to customers based on infrastructure. I derive information on local mobile infrastructure improvements from the electromagnetic spectrum licenses the Federal Communication Commission issues to mobile network operators. Both datasets exhibit a high degree of geographical (county) and temporal (year) variation that is pivotal for my identification strategies.

I begin by providing evidence on the introduction of mobile technology spurring competition across banks. Within a county, institutions that do not provide mobile banking services witness significant deposit outflows following local mobile infrastructure improvements. At the same time, institutions that provide mobile banking services witness significant deposit inflows. The opportunity cost of not having an app to bank with increases with the infrastructural improvement, which prompts smoother and more extensive usage of mobile apps in general. Some customers subject to this opportunity cost then appear to switch to better-digitalized banks as it rises beyond their liking. Results withstand controlling for local, time-varying economic conditions through the progressive loading of controls and fixed effects.

These patterns prompt me to investigate mobile technology adoption, the timing of which varies across banks leading to changes in the competitive environment and, ultimately, a reallocation of deposits. Using hazard and linear regression models, I find banks adopt mobile technology earlier when their customer base is young and educated. Furthermore, the *bank type*—which I define based on geographical reach, size, and scope of operations—plays an important role in mobile technology adoption. *Big community banks* (assets above \$1 billion, yet local reach), *large banks* (assets above \$1 billion, regional/national reach), and the *big 4 banks* (Bank of America, Chase, Citi, Wells Fargo) appear to adopt mobile technology in a timely matter. On the other hand, *small community banks* (assets below \$1 billion, local reach) are much slower to adopt the technology. Additionally, anecdotal evidence found while collecting the app data suggests the apps of small community banks are often lower quality than the apps of their larger competitors. Overall, I gather *bank type* is a strong determinant of app adoption and app quality. Further, *bank type* is arguably unrelated to the timing of mobile infrastructure improvements.

Building on intuition from the two sets of results just presented, I proceed to show that it is indeed (under-digitalized) small community banks that experience significant deposit outflows following improvements in the county's mobile infrastructure. At the same time, it is (better-digitalized) non-community banks that experience large deposit inflows in the county.

Further, I show small community banks lower their deposit spreads after the improvements. With their superior technology, larger banks attract those depositors at the margins that the infrastructural improvement turns digital-savvy by raising the opportunity cost of staying with an under-digitalized bank. At a technological disadvantage, small community banks have to increase deposit rates instead. Additionally, these dynamics are associated with a significantly higher likelihood of branch closure for small community banks. Mobile banking is acting as a *de facto* negative technological shock for these institutions.

Given that small community banks are the ones negatively affected by this novel technology-spurred competition, I shift my focus to the asset side of their balance sheet. Existing literature suggests that small community banks have a competitive advantage in small business lending (Petersen and Rajan (1994), Cole et al. (2004), Berger et al. (2005), Carter and McNulty (2005)). Unlike bigger banks, they entertain close relationships with their customers from which they extract useful knowledge for their lending decisions. Deposits are crucial in this process because they constitute both a source of information (Agarwal and Hauswald (2010), Li et al. (2019)) and of stable funding (Drechsler et al. (2017), Li et al. (2019)). Therefore, I argue the loss of deposits linked to the advent of mobile technology hampers small community banks' small business lending activity. Other lending activities employ more liquid and standardized products instead. Given that they are less reliant on deposits' soft information and stable funding, I posit that they should not respond to the technology shock as much.

I show small community banks reduce their small business lending substantially once the technology shock hits. A significant improvement in a county's mobile infrastructure results in a 15% decrease in the total amount of small business lending from local small community banks. Further, small community banks without a mobile banking app are driving this decrease, confirming the digitalization channel. Small community banks also reduce the percentage of nonperforming small business loans on their balance sheet. In the meantime, they keep their other lending positions—mortgages, student loans, car loans, and so on—virtually unchanged.

I then proceed to investigate whether other players fill this lending gap. Bigger banks gain deposits after mobile infrastructure upgrades. However, I show they only increase their small business lending if they are digitalized and in areas where they do no directly operate branches. The fact that they do not increase their lending locally is not entirely surprising, given these institutions are known for their transactional approach and reliance on hard information (Cole et al. (2004), Berger et al. (2005), Uchida et al. (2012)). Within the context of small business lending, deposits do not carry the same information and liquidity advantages for them as they would for small community banks. FinTech firms seem to make up for a little of the decrease as well, almost exclusively in metropolitan areas.[1]

I conclude by showing the local economy benefits less from digitalization and mobile services in areas where small community banks had an important presence before their introduction. Positive and significant coefficients on mobile infrastructure improvements for various measures of local economic growth suggest digitalization per se spurs economic activity. However, the interaction of mobile infrastructure improvements with the local share of small community bank deposits before the development of mobile technologies carries negative and significant coefficients. Furthermore, small community banks display much stronger growth-counteracting power in rural areas. This dynamic seems to align with the previous pattern of FinTech firms not picking up small business lending in such areas.

Given these findings, the paper contributes to four major strands of literature.

First, the paper shows how mobile technology is changing relationship lending through its impact on relationship lending's most prominent advocates, namely, small community banks. Abundantly covered in the literature, small community banks have an advantage in

[1] Using data from UCC Filings courtesy of Gopal and Schnabl (2020), I highlight a partial substitution between banks and FinTech firms over the 2010-2016 timeframe.

conducting this kind of lending with small businesses (Petersen and Rajan (1994), Berger and Udell (1994), Cole et al. (2004), Berger et al. (2005), etc.). Additionally, the general consensus has been they can rely on this advantage to remain competitive going forward (DeYoung et al. (2004), Carter and McNulty (2005), Bongini et al. (2007)). However, I show the advent of mobile technology deprives small community banks of this advantage through deposit outflows. As a result, a significant amount of relationship lending is now getting lost. Related, I argue a way to circumvent this loss could be the exploitation of economies of scale within the community bank model.[2] My analysis shows big community banks are faring digitalization well. In particular, they continue undisturbed in their sizable small business lending activities.[3] A shift towards larger community banks could help keep small businesses' credit access unchanged.

Second, this paper provides insights into the resilience of the traditional commercial bank business model to digital shocks. This business model is characterized by the incorporation of both deposit-taking and lending activities within the same institution. Thus far, this feature has proven beneficial thanks to the synergies between the two. Norden and Weber (2010), Agarwal and Hauswald (2010), and Yang (2021) have highlighted synergies of an informational nature, whereby account activity contains information on borrower risk and local economic outlooks that banks use in their lending decisions. Drechsler et al. (2017), Li et al. (2019), and Drechsler et al. (2021) have highlighted liquidity and interest rate synergies, whereby higher deposit market power shields banks from rate changes and funding cyclicality. Due to the opaqueness of the market and their relationship-based approach, small community banks are particularly reliant on these synergies in their small business lending. Additionally, the analysis shows they only reduce this kind of lending following

[2]To my knowledge, only two other papers highlight the usefulness of these economies of scale (Hughes et al. (2016), Hughes et al. (2019)). They do so from the performance point of view.

[3]Recent literature has suggested these activities are more relationship than transaction-based (Nguyen and Barth (2020) and FDIC (2020a)).

technology-driven deposit outflows. Therefore, the introduction of mobile technology seems to be stripping these institutions of precisely the core synergies just mentioned. This result further questions the reliability of the traditional bank business model going forward, under more digital disruption. Timely adoption of new technologies appears key.

Third, this paper contributes to the literature on the rise of financial services digitalization. So far, the focus has been on FinTech firms gaining momentum thanks to technological innovation (Buchak et al. (2018), Fuster et al. (2019), Boot et al. (2021)), a reduced presence of traditional banking (Erel and Liebersohn (2020)), and increased bank regulation (Buchak et al. (2018), Gopal and Schnabl (2020)). Little research has investigated the adoption of new technologies by traditional commercial banks instead. Dante and Makridis (2021) explore mobile banking usage in relation to banks' physical presence. Closer to this paper, Jiang et al. (2022) set up a model of banking competition under digital disruption where only a fraction of banks digitalize. Despite the similar setting, I investigate a different research question. Jiang et al. (2022) focus on the impact of traditional commercial banks' digitalization on financial inclusion; I focus on how digitalization is reshaping the banking sector. Compared with these studies, I introduce new data that allow me to fully identify mobile technology adoption and investigate its consequences for the entire universe of U.S. depository institutions.

Lastly, the paper contributes to the literature on the consequences of bank branch closures. In its more recent developments, this literature has focused on financial inclusion (Brown et al. (2019), Jiang et al. (2022)) and local lending conditions (Nguyen (2019), Ho and Berggren (2020), Bonfim et al. (2021)). This paper directly links recent bank branch closures with digitalization and highlights the importance of distinguishing the type of bank closing branches to fully grasp economic consequences.

2 Data

I maintain a 2010–2019 sample that covers the evolution of mobile technology and its adoption by banks outside the financial crisis and the COVID-19 pandemic. I consider the universe of U.S. insured depository institutions, relying on FDIC Summary of Deposits data for branch-level information and FFIEC Call Reports data for institution-level information. I then use three other main sets of data: mobile banking app data, mobile infrastructure improvements data, and small business lending data. Lastly, I derive county-level controls from Census Bureau, Bureau of Labor Statistics, and Bureau of Economic Analysis data. In what follows, I thoroughly describe how I derive mobile banking app data and mobile infrastructure improvements data. I then illustrate the need for three different data sources in small business lending analysis.

2.1 Mobile banking data

I hand-collect data on when each U.S. depository institution started providing mobile banking services. From a joint search of the institution's website and the data.ai platform,[4] I extrapolate the launch dates of banks' first mobile banking apps. Data.ai is an online platform that provides developers with marketing intelligence data on their own apps and their competitors' apps across Google Play (the Android app market) and the App Store (the iPhone app market). Its proprietary search engine enabled me to manually look up each bank and see the first time it released a consumer banking app. While collecting these data, I noticed a pattern worth mentioning. Especially earlier in the sample, the same institution would launch its Apple app before its Android one. This pattern is likely because programmers back then had a harder time developing apps compatible with the large variety of Android smartphones. Further developments in the Android system itself and standardiza-

[4] Data.ai website.

tion across smartphone brands make this less of an issue today. To be conservative, in the analysis, I thus use the variable $app\ available_{b,t}$, which captures whether the bank has an app available in at least one of the two stores.

2.2 Mobile Infrastructure data

I derive a proxy for local improvements in mobile infrastructure from the universe of Federal Communication Commission (henceforth FCC) licenses. The FCC regulates the usage by private and public entities of the *electromagnetic spectrum*, which is "the range of electromagnetic radio frequencies used to transmit sound, data, and video across the country" (FCC website). That is, the non-visible frequencies of the electromagnetic spectrum allow the transmission and reception of data between devices such as radios, smartphones, and TVs and are regulated by the FCC. Given the growing popularity of mobile communication and smartphone technology over the last decade, the agency has dedicated more and more parts of the spectrum to mobile network operators (henceforth MNOs). In particular, 3G and 4G technologies operate through the frequencies belonging to the following parts of the spectrum (defined in terms of *MHz bands*)[5]:

- 600MHz: repurposed from TV broadcast;
- 700MHz Service: comprising WCS (Wireless Communications Service), Upper Band, Lower Band;
- Cellular: 824–849 and 869–894 MHz Bands;
- SMR (Specialized Mobile Radio) service: comprising 800 Auctioned SMR, 900 Auctioned SMR;

[5] *MHz* stands for "a unit of frequency equal to one million hertz" (Merriam-Webster).

- PCS (Personal Communication Service) Broadband: 1850-1990 MHz Band comprising Broadband PCS, Broadband PCS G block 1910-1915 and 1990-1995 MHz Bands Market Area;
- AWS (Advanced Wireless Services): comprising AWS-1 1710-1755 and 2110-2155 MHz Bands, H Block 1915-1920 and 1995-2000 MHz Bands, AWS-3 1695-1710 1755-1780 and 2155-2180 MHz Bands, AWS-4 2000-2020 and 2180-2200 MHz Bands;
- 2.5 GHz: comprised of Broadband Radio Service, Educational Broadcast Radio Service.

The FCC manages these bands through a licensing system. FCC licenses guarantee MNOs the exclusive use of certain frequencies in these bands (i.e., a set amount of MHz within the band) over geographically defined market areas. They are allotted to MNOs and their subsidiaries through auctions managed by the agency itself. Once an MNO secures license ownership through an auction, it can decide when to activate the license. From the effective date of activation, the license is then going to last ten years, with options for renewal. Whereas different MHz bands serve different purposes in cell phone data transfer, MNOs always use a mix of them to guarantee cell phone service across their geographies.[6] Therefore, having more frequencies in these bands generally translates into the ability to satisfy more customers at higher speeds.

Ideally, I would reconstruct how many frequencies MNOs have—in technical jargon, the *spectrum holdings* of MNOs—and use their developments over the sample period to track mobile infrastructure evolution. However, this approach would require the historical of mobile FCC licenses since the late '80s, whereas the FCC only allows the bulk download of currently active licenses.[7] Additionally, active licenses include both licenses that have been activated for the first time during the previous ten years and licenses that have been

[6]For example, lower frequencies provide extensive coverage at the expense of data capacity, and higher frequencies have more capacity but lower geographical penetration.

[7]FCC License View.

renewed during the previous ten years, with no direct distinguishing across them from the data. Notwithstanding, certain MHz bands were only made available to MNOs through auctions that took place during my 2010–2019 sample period.[8] Further, these newly released MHz bands are the ones that led to the quadrupling of the amount of spectrum devoted to mobile communication over the last decade in response to the growing consumer demand for smartphones and streaming services.[9] Therefore, I focus on licenses in these bands alone and reconstruct the *spectrum expansions* that happened between 2010 and 2019. In light of the above, these expansions should be as good a proxy for mobile infrastructure improvements as directly tracking the evolution of total spectrum holdings, especially under geography fixed effects.

In detail, I secured the license data in mid-2021. Given the life span of licenses and the lag in data publication, I can therefore go back in time as far as 2010. From these data, I single out mobile licenses in the newly granted bands. For each of these licenses, I calculate the corresponding spectrum expansion as the amount of MHz between the reported *frequency assigned* and *frequency upper band* (as per FCC definitions). Because licenses are granted over geographical market areas that have conversion tables to counties, I am able to link each license to the counties it pertains to. I then derive for each county each year the total amount of spectrum expansions that MNOs have achieved since 2010. Table 1 reports descriptive statistics for these expansions in 100s of MHz, and Figure 1 maps them out over time. The expansions have sped up in the second half of the sample due to some important FCC auctions in 2014, 2015, and 2016. They display different paces across different geographies. Throughout the analysis, I use as measures both county-level spectrum expansions in 100s

[8] The newly granted MHz bands are 600MHz, 700MHz, AWS, and 2.5 GHz.

[9] This fact also reflected in the prices paid by the auction winners—the highest ever—and the quick activation of the corresponding licenses (Source: FCC Auctions Summary, contacts in the industry, and anecdotal evidence).

of MHz since 2010 ($sp.\ expansion_{\ c,t-1}$) and whether the county's spectrum expansions are above the current country median ($sp.\ exp.\ above\ Y - median_{\ c,t-1}$).[10]

2.3 Small business lending data

Because there is no detailed-enough public data covering all the lenders involved in the small business lending market at once, I have to split the analysis based on the different lender types—small community banks, bigger banks, FinTech firms—and separately investigate their behavior within the scope of the corresponding dataset.

For banks below \$1 billion in assets, I use FDIC Call Report entries regarding commercial and industrial loans below \$1 million. Recent industry studies consider this balance-sheet measure a good proxy for small business lending at small banks (e.g., FDIC (2020b)).

For larger banks, I follow the literature and use Community Reinvestment Act (CRA) data. CRA reports are filed yearly and are mandatory for banks with assets above a predetermined threshold ($\sim$ \$1.1-1.2 billion during my sample period). They cover originations of small business loans by bank and borrower location.[11]

Additionally, I use small business lending data courtesy of Gopal and Schnabl (2020). The authors derive these data from UCC filings, that is, filings routinely registering the non-real estate collateral of small business loans. Therefore, they cover secured (non-real estate) loan originations from 2010 to 2016. They have the value added of including FinTech lenders. I use them to compare bank and FinTech dynamics in small business lending during at least a part of my sample's time frame.

[10]Significant variation exists in this latter variable as well, with 0.65% of the counties experiencing a change in its value at least once during the sample's time frame.

[11]To be noted that they consider originations also credit card lines and their extensions.

3 Technology-spurred competition on deposits

The recent trend in financial services digitalization has introduced new external competition for banks in the form of FinTech firms (e.g., Buchak et al. (2018), Gopal and Schnabl (2020)). This section investigates whether it has also reshaped competition within the traditional commercial banking sector. Commercial banks are not just witnesses to the rise of FinTech, they are trying to increase their own digital footprint to keep up with the times. One obvious way they have started doing so is by offering mobile banking services. If depositors find value added in such services and there is heterogeneity in the extent to which depository institutions can provide them, then such institutions might find themselves in competition with each other on one additional dimension that was previously absent.

To verify whether this is the case, I start by analyzing deposit patterns around mobile infrastructure improvements. An improvement in mobile infrastructure enables a wider usage of mobile apps of better quality. As such, it should prompt an increase in technology-spurred competition across banks. To analyze banks' dynamics around this increase, I employ the following year-county-bank-level identification strategy:

$$\begin{aligned} ln(outcome\ variable_{b,c,t}) = \alpha_c + \alpha_t + \beta_1\ spectrum\ expansions_{c,t-1} + \beta_2\ app\ available_{b,t-1} \\ + \beta_3\ spectrum\ expansions_{c,t-1} * app\ available_{b,t-1} + \gamma X_{c,t-1} + \epsilon_{b,c,t}, \quad (1) \end{aligned}$$

where *outcome variable*$_{b,c,t}$ is either the logarithm of deposits or the deposit pricing of bank b in county c and year t. *Spectrum expansions*$_{c,t-1}$ capture mobile infrastructure improvements in county c and year $t-1$ in terms of 100s of MHz of new electromagnetic spectrum allotted to mobile network operators, and *app available*$_{b,t-1}$ is a dummy variable equal to 1 if bank b has an app on either Google Play or the Apple Store in year $t-1$. α_c represent county fixed effects, α_t are year fixed effects, and $X_{c,t-1}$ is a set of lagged county-year and bank-year controls. County-year controls include population, GDP, income per capita, employment rate, and number of businesses. Bank-year controls include the number of bank b branches in the county, the ratio of nonperforming loans to assets, the ratio of net income to assets, a dummy variable taking the value of one if the branch(es) the bank operates in the county have been established more than 43 years before (sample median) to capture a long tradition of serving the community, the number of counties the bank operates in. This specification focuses on the differential effect of having an app at the time of the infrastructural improvement. Being able to provide mobile banking services should become relatively more valuable after the improvement, given the customer's opportunity cost of staying with a bank that does not provide these services increases as they improve and become more popular.

First, Panel A of Table 3 reports estimation results for the above specification with the logarithm of deposits as the dependent variable. It shows only banks that provide mobile banking services at the time of the infrastructural improvements experience deposit growth (positive and significant interaction of $\textit{spectrum expansions}_{t-1}$ with $\textit{app available}_{t-1}$, the main coefficient of interest). At a higher competitive disadvantage after the improvements, banks without an app lose significant amounts of deposits instead (negative coefficient on $\textit{spectrum expansions}_{t-1}$). Overall, some depositors seem to prefer better-digitalized banks after local mobile infrastructure improvements. Column 1 shows that a significant increase in $\textit{sp. expansions}_{c,t-1}$ of 100MHz—like the one that happened for many counties between 2015 and 2017—results in a 8.88% increase in deposits at banks that provide a mobile banking app and a 5.92% decrease in deposits at banks that do not provide an app. Column 2 shows that results remain consistent under bank type x year fixed effects. Here, banks are classified as either small community banks, big community banks, large banks, or the big four (Bank of America, Chase, Citi, Wells Fargo).[12] Therefore, the fixed effects aim

[12]Please refer to the next section for a thorough explanation of this classification.

at controlling for time trends and changes in regulation for these different types of banks. Column 3 introduces county x year fixed effects, which control for changes in local demand over time but also absorb the baseline effect of $spectrum\ expansions_{t-1}$. The coefficient of interest on the interaction of $spectrum\ expansions_{t-1}$ with $app\ available_{t-1}$ remains positive and significant. Not pictured, results remain robust to the addition of bank fixed effects throughout these specifications. However, under bank fixed effects the magnitude of the coefficient of interest is generally lower due to the fact that 29.55% of the observations in the sample belong to banks that either always have or never have an app in the sample's timeframe (whose variation in $app\ available_{t-1}$ is then absorbed by the bank fixed effect). In column 4, I randomize mobile infrastructure improvements within each county over time in a placebo test, and the coefficient of interest loses significance.

Panel B of Table 3 presents results on deposit pricing. The analysis is run at the quarter-county-bank level, with deposit spreads calculated as the difference between the Fed Funds Rate and the county-bank average of the Money-Market 25-year rates at rate-setting branches from RateWatch. The specifications across columns 1 to 4 mirror those in Panel A, albeit under quarterly frequency. Overall, there is evidence that banks become more sensible to changes in the Fed Funds Rate when the local mobile infrastructure improves (large, negative and significant coefficient on $spectrum\ expansions_{t-1}$ in columns 1 and 2). However, banks that provide mobile banking services gain on average less sensibility than those without a mobile banking app upon mobile infrastructure improvements (smaller, positive and significant coefficient of interest on the interaction of $spectrum\ expansions_{t-1}$ with $app\ available_{t-1}$ in columns 1 and 3). Not pictured, results remain robust to the addition of bank fixed effects throughout these specifications. Again, under bank fixed effects the magnitude of the coefficient of interest is generally lower due to the fact that around 30% of the observations in the sample belong to banks that either always have or never have an app. The placebo test in column 4 gives non-results for deposit pricing as well.

Overall, banks that provide mobile banking services use their superior technology to attract digital-savvy depositors and increase their market power. At a technological disadvantage, banks that do not provide banking services lose customers and are forced to cut prices. These findings confirm the conjecture that mobile technology has introduced a new dimension along which banks compete. However, why certain banks have not been timely in their mobile technology adoption to the point that they lose clients remains unclear. In the next section, I investigate mobile technology adoption dynamics with the help of hazard and linear regression models.

4 Mobile technology adoption

I first consider what elements might be influencing the timing of mobile technology adoption.

One element could be the composition of the customer base. Younger customers might be more drawn to mobile services than older ones. The 2019 FDIC Survey of Household Use of Banking and Financial Services reports that around 60% of individuals ages 15 to 34 use mobile banking as their primary method to access their bank account, against only 8.3% ages 65 or more. According to the same study, highly educated individuals are also more likely to use mobile banking. Banks with a younger and highly educated customer base could then be prone to faster adoption.

Another element could be the quality of the mobile infrastructure in the geographies the bank covers. Certain banks might wait to launch a fully-fledged app until they are certain their customer base can have full access to it.

More related to the bank's ability and willingness to invest in new technology, bank performance could also be playing a role.

A fourth element could be the type of bank making the decision. Larger banks have a clear advantage in the upfront investment required to adopt and maintain mobile banking technologies. Banks with broader geographical coverage might have an incentive for early adoption because they are susceptible to a larger number of competitors and mobile infrastructure of varying quality. Banks relying on in-person interactions with their customers might not see the need for this kind of technology in their operations instead. Therefore, I set up a framework that considers banks across the three main dimensions of size, geographical coverage, and scope of operations. I categorize depository institutions with total assets below $1 billion as *small community banks*. These banks are small and known to be highly reliant on the soft information they gather through repeated interactions with their customers. Building on FDIC (2012), I then categorize as *big community banks* depository institutions that satisfy the following conditions: (i) total assets above $ 1 billion, (ii) loans to assets $> 33\%$, (iii) deposits to assets $> 50\%$, (iv) 75 branches at most, (v) number of large metropolitan statistical areas with branches < 3,[13] (vi) number of states with branches < 4, and (vii) no branches with more than $ 5 billion in deposits. This category captures institutions that did embrace some economies of scale but kept within the boundaries and the modus operand of the community bank business model.[14] I maintain a separate category for the *big 4 banks* - Bank of America, Chase, Citi, Wells Fargo. All other depository institutions enter the residual category of *large banks*. These institutions are mainly banks with regional or national coverage, known to be highly reliant on hard information in their decision-making and to maintain a transactional approach with their customers.

I then investigate the weight that each of these elements—customer base, mobile infrastructure quality, bank type—carry in the decision to adopt mobile technology. Table 4,

[13] A large metropolitan statistical area is defined as a metropolitan statistical area with more than 500,000 inhabitants.

[14] Such institutions have been shown to significantly contribute to small business lending and to present more community bank-like traits than larger counterparts (Hughes et al. (2016), Nguyen and Barth (2020)).

Panel A, presents hazard ratios from a parametric hazard model run across all banks, where the end event is the adoption of the app.[15] In other words, the model captures whether each of the different elements above results in quicker or slower app adoption. Hazard ratios above 1 represent quicker app adoption, and hazard ratios below 1 represent slower app adoption. Therefore, estimates show an older customer base slows down app adoption, whereas a highly educated one speeds it up.[16] Further, big community banks and large banks are much faster than small community banks in adopting mobile banking technology.[17] Bank health and performance do not seem to influence much the timing of mobile technology adoption. Interestingly, mobile infrastructure improvements, a deposit-weighted average of $spectrum\ expansions_{c,t}$ across the counties the institution operates in, seem to slow adoption down.

For an additional test of these trends in the same spirit of the hazard model, I employ the following year-bank-county-level linear regression model:

$$\begin{aligned}\%\ branches\ providing\ app_{c,t} = \alpha_s + \alpha_t + \beta_1\ spectrum\ expansions_{c,t-1} + \\ \beta_2\ county\ demographics_c + \beta_3\ county\ banking\ characteristics_{c,t} + \epsilon_{c,t}, \quad (2)\end{aligned}$$

where the dependent variable $\%\ branches\ providing\ app_{c,t}$ is the number of county c year t branches belonging to banks that provide a mobile banking app over total county c year t branches. Among the independent variables, $spectrum\ expansions_{c,t-1}$ capture mobile infrastructure improvements in county c and year $t-1$ in terms of 100s of MHz of new elec-

[15]The model is calibrated on a Weibull survival distribution to take into account that the likelihood of getting an app increases over time as the service becomes more and more popular.

[16]I compute the likelihood of an older customer base as the deposit-weighted average of the local percentage of people ages 65 and older across the counties the bank operates in. I compute the likelihood of a highly educated customer base as the deposit-weighted average of the local percentage of people with higher education across the counties the bank operates in.

[17]The big 4 banks do not enter these models as they already had an app before or just got one at the start of the sample's timeframe.

tromagnetic spectrum allotted to mobile network operators. $County\ demographics_c$ include share of population ages 65 and older and share of population that received higher education as per the 2010 Census. $County\ banking\ characteristics_{c,t}$ include $I(big\ comm.\ bank\ branches_{c,t})$ and $I(non\text{-}comm.\ bank\ branches_{c,t})$, dummies for the presence of at least one big community bank branch in county c at year t and the presence of at least one non-community bank branch, respectively. This specification includes state fixed effects and year fixed effects.

In Panel B of Table 4, column 1 shows a one-standard-deviation increase in the share of population 65 and older in the county (5.18%) reduces the % branches providing an app in the county by 5.8% with respect to the unconditional sample mean (53.12%). At the same time, a-one-standard-deviation increase in the share of highly educated population (7.31%) increases the % branches providing an app in the county by 6.90% with respect to the unconditional sample mean. Interestingly, $spectrum\ expansions_{c,t-1}$ continue to play a deterring role in app adoption. In column 2, I add $I(big\ comm.\ bank\ branches_{c,t})$, $I(large\ bank\ branches_{c,t})$, $I(big4\ bank\ branches_{c,t})$ to the specification. The addition raises the within-R-square from 4.76% to 11.2%. The presence of big community banks, large banks, and big 4 banks carries positive and significant coefficients. Having a big community bank in the county raises the percentage of branches that provide mobile banking apps in the county by 7.66% with respect to the unconditional sample mean. Having a big4 bank in the county raises the percentage of branches that provide mobile banking apps by 18.11% with respect to the unconditional sample mean. Having a large bank in the county raises the percentage of branches that provide mobile banking apps by 14.44% with respect to the unconditional sample mean. Columns 3 and 4 repeat the analysis with the percentage of deposits held at banks that provide apps as dependent variable instead. Patterns are similar. Local spectrum expansions are again confirmed to carry a negative weight in app adoption.

In Panel C, I investigate the role of $spectrum\ expansions_{c,t-1}$ to better understand what is driving this negative association with the timing of app adoption. More in detail, I replicate the model in equation 2 with three different dependent variables. Column 1 looks at the number of county branches belonging to small community banks that provide a mobile banking app over total small community bank branches in the county. Column 2 looks at the number of county branches belonging to big community banks that provide a mobile banking app over total big community bank branches in the county. Column 3 looks at the number of county branches belonging to large and big 4 banks that provide a mobile banking app over total non-community bank branches in the county. These specifications investigate how each bank type relates to mobile infrastructure improvements in its app adoption. They are motivated by the fact that different bank types could relate differently to local infrastructural improvements. For example, with wide geographical coverage and abundant financial resources, larger banks might have an incentive for earlier adoption to beat competitors and less sensitivity to local infrastructural conditions. The panel demonstrates that the negative effect of mobile infrastructure improvements highlighted in the previous two models is in fact only driven by small community banks. This finding could be related to infrastructural improvements allowing for higher-quality apps that become increasingly difficult for these banks to develop. Small community banks might be discouraged from adopting the new technology in the first place. That said, economic magnitudes of this effect are close to insignificant as an important increase in $sp.\ expansions_{c,t-1}$ of 100MHz results in a decrease in the share of branches that offer mobile banking services across local small community banks of just $\sim$3%.

In general, the evidence gathered so far points to bank type as a crucial component in timely app adoption and at small community banks as particularly slow adopters. Figure 2 provides the ultimate proof of concept. It simply plots the percentage of banks providing an app within each bank-type category over time. It shows that, at all times within my sample, small community banks have been trailing behind the other two bank types in providing mobile banking services. Interestingly, big community banks—operating on a similar business model but at a larger scale—are faring digitalization well. The big 4 banks have been at the forefront of digitalization, while large banks fare well at first and then slow down. This pattern is likely due to the residual nature of large bank category. It contains big national banks that have been early adopters and account for the initial high levels of app adoption. It also contains foreign banks and institutions that mainly provide wealth-management services. As such, they have less use for commercial banking apps and are likely producing the subsequent slack.

These dynamics align with survey work conducted by the FDIC, where small community banks emerge as challenged in the adoption of new technologies on the cost side (FDIC (2020a)). The cost of developing an app might not seem high upon first consideration. Online anecdotal evidence suggests building a mobile banking app costs between $500,000 and $1 million. However, related expenses might carry significant weight. App quality and extended app functionalities, updating legacy systems to have customer data neatly aligned for input, app updates, being part of other popular digital networks such as Apple Pay, and so on could significantly increase the cost. Another element that might be contributing to these patterns comes from the scope of small community banks' operations. These banks have always relied upon building close relationships with their clients through repeated human interaction. Some of them might not anticipate their clients' desire for digital services or might miscalculate its weight.

Overall, the analysis reveals that bank type is an important determinant of timely app adoption. In particular, all tests point to small community banks being the slowest adopters. Furthermore, during the manual collection of banking apps' launch dates, I got the sense that even if available, small community banks' apps generally offer fewer services and updates with respect to larger banks' apps.[18] Because bank type is an important determinant

[18] Hand collection of app quality data is unfeasible. I am working to find an alternative way to obtain them.

of app adoption, arguably unrelated to mobile infrastructure improvements and capturing additional information on app quality, I will use it as a proxy for mobile technology adoption throughout the remainder of the analysis. Specifically, I will first build on the competition analysis in Section 3 and show that substituting *app available* with *bank type* leads to virtually the same results—i.e., it is primarily small community banks that do not have an app and lose deposits to larger banks with an app. From there, I will proceed to focus on small community banks as the ones most negatively impacted by mobile-technology-spurred competition. I will show they decrease their small business lending and close branches in response to local mobile infrastructure improvements. At the same time, bigger banks and FinTech firms are not able to fully substitute for them within the context of the small business lending market. I will conclude by discussing the effects of these dynamics on the local economy.

5 Consequences for small community banks

Considering Section 3 and Section 4 together, results would suggest that it might be small community banks that lose deposits to larger, better-digitalized banks following mobile infrastructure improvements. In order to investigate whether this is the case, in Table 5 I re-run equation 1 substituting $\textit{app available}_{b,t-1}$ with $\textit{bank type}_{b,t}$. Columns 1 and 2 of Panel A show that it is indeed small community banks that lose deposits to larger, better-digitalized banks following mobile infrastructure improvements. In particular, the negative and significant coefficient on $\textit{sp. expansions}_{c,t-1}$ remains quite close to its counterpart in Table 3. Under the new specification, a significant increase in $\textit{sp. expansions}_{c,t-1}$ of 100MHz—like the one that happened for many counties between 2015 and 2017—results in a 9.27% increase in large bank deposits and in a 14.37% increase in big 4 bank deposits (column 1). Big community banks do not appear subject to the same outflows as small community banks in column 1, but the introduction of bank type x year fixed effects in the following columns seems to explain this result away. Further, column 3 confirms that results with $bank\ type_{b,t}$ still mirror results with $app\ available_{b,t-1}$ under the inclusion of county x year fixed effects. Panel B repeats the exercise with deposit spreads as the outcome variable. Estimates further confirm that it is indeed small community banks that become the most sensible to changes in the Fed Funds Rate after local mobile infrastructure improvements (negative and significant coefficient on $sp.\ expansions_{c,t-1}$, quite close to its counterpart in Table 3).

Overall, these estimates paint a picture where larger banks use their superior technology to attract additional digital-savvy depositors following local mobile infrastructure improvements. At a technological disadvantage, small community banks lose customers instead and are forced to lower their deposit spreads. Therefore, I proceed to investigate the consequences from the small community bank point of view.

In contrast to bigger banks, small community banks (henceforth SCBs) are known to build relationships with their clients that enable them to acquire soft information they efficiently use in their lending decisions (Cole et al. (2004), Carter et al. (2004), Berger et al. (2005), Carter and McNulty (2005)). Such relationships are built through repeated interaction on loans and the cross-sale of related services like accounts and cash management (Petersen and Rajan (1994), Berger et al. (2005), Mester et al. (2007)). Indeed, more recent literature has focused on accounts and the deposit franchise in their synergies with lending. On the one hand, it has highlighted informational synergies. Monitoring deposits conveys information on the financial well-being of the customer (Mester et al. (2007), Norden and Weber (2010)) and the economy at large (Yang (2021)). On the other hand, it has uncovered liquidity and interest rate synergies. Deposits are a stable source of funding and hedge against interest rate risk (Drechsler et al. (2017), Li et al. (2019), Drechsler et al. (2021)). In this paper's context, technology-driven deposit outflows should then cause SCBs to lose some of their informational insights and liquidity advantages. This effect would make operating in more opaque and illiquid markets, such as the small business lending one, especially difficult. Therefore, I expect SCB small business lending to be negatively affected by the deposit outflows outlined in the previous section more than other types of lending.

To test this hypothesis, I employ the following year-bank-county-level specification:

$$ln(lending\ amount_{b,c,t}) = \alpha_b + \alpha_c + \alpha_t + \beta_1\ spectrum\ expansions_{c,t-1} + \gamma X_{c,t-1} + \alpha_c + \epsilon_{b,c,t}, \quad (3)$$

where *lending amount*$_{b,t}$ is the amount of small business/real estate/individual/other lending on the balance sheet of SCB b in year t. The source of these lending data are FDIC Call Reports at the institution level, with small business lending being reliably proxied by Commercial and Industrial Loans below \$1 million (FDIC (2020b)). To allow for my county-level mobile infrastructure improvement measure (*sp. expansions*$_{c,t-1}$) and further local economic controls, I link these institution-level data to the county c the small community bank b has most of its deposits in in year t. Because more than 90% of SCBs have most of their deposits in one county, the measurement error should be minimal. Then, α_b represent bank fixed effects, α_c are county fixed effects, α_t are year fixed effects, and $X_{c,t-1}$ is a set of lagged county-year and bank-year controls. County-year controls include population, GDP, income per capita, employment rate, and number of businesses. Bank-year controls include the number of bank b branches in the county, the ratio of nonperforming loans to assets, the ratio of net income to assets, a dummy variable taking the value of one if the branch(es) the bank operates in the county have been established more than 43 years before (sample median) to capture a long tradition of serving the community, the number of counties the bank operates in.[19]

[19] I still maintain county fixed effects to control for time-invariant county characteristics estimated on the entire sample time span, including the level of spectrum in each county at the start of the sample that I am not able to account for with my *spectrum expansions* measure (please refer to section 2.2 for more information).

Panel A of Table 6 reports regression estimates for small business lending in column 1, real estate loans in column 2, individual loans in column 3, and other loans in column 4. As expected, the only significant coefficient on *spectrum expansions*$_{c,t-1}$ is in the small business lending specification, and it is negative. A significant increase in *sp. expansions* of 100MHz—like the one that happened for many counties between 2015 and 2017—results in approximatively a 7.54% decrease in the small business lending reported on the balance sheet of active SCBs.

In Panel B of Table 6, I investigate the digitalization channel, whereby the decrease in small business lending at small community banks is a consequence of the departure of digital-savvy depositors outlined in the previous section. To do so, I proceed in stages. In column 1, I replicate the main result of Eq. 3 for reference. In column 2, I again randomize mobile infrastructure improvements within each county over time in a placebo test. Results lose significance upon the randomization of timing of the improvements, confirming the link between the decrease in small business lending and mobile infrastructure improvements. In column 3, I introduce *app available*$_{b,t-1}$ in interaction with *spectrum expansions*$_{c,t-1}$. If the decrease in small business lending is due to the outflow of digital-savvy depositors, I would expect a positive and significant coefficient on this interaction (small community banks with mobile banking apps should lose less depositors). In this test, I forego bank fixed effects as they would absorb high amounts of variation I am highly interested in, which is the one coming from banks that never adopt an app.[20] Estimations confirm the digitalization channel, with a positive and significant coefficient on the interaction of *app available*$_{b,t-1}$ with

[20]Including bank fixed effects in column 3 significantly decreases the magnitude and erases significance in the coefficient of interest. This suggests that app adoption by small community banks does not lead to higher small business lending per se under mobile infrastructure improvements, rather it shields the bank from a small business lending decrease with respect to other small community banks, many of which do not adopt an app in the first place. This make sense given that the apps adopted by small community banks are hardly at the forefront of quality - they might prevent certain depositors to leave, but won't help in gaining more.

spectrum expansions$_{c,t-1}$. In column 4, I control for time-varying local economic conditions and results remain robust.

In light of these findings, I further investigate whether SCBs become warier in providing credit to risky small businesses. Such a move could be related to the market becoming more opaque for them under the informational loss that accompanies deposit outflows. To test this possibility, in Panel C of Table 6, I re-employ equation 3. However, the dependent variables are now the share of nonaccrual commercial and industrial loans (column 1), the share of still-accruing commercial and industrial loans at least 30 days past due (column 2), and the share of commercial and industrial loans charge-offs (column 3). I show that the first two present decreasing patterns after improvements in the local mobile infrastructure.[21] A significant increase in *sp. expansions*$_{c,t-1}$ of 100MHz—like the one that happened for many counties between 2015 and 2017—results in approximately a 43% (33.8%) decrease in the share of nonaccrual (still-accruing at least 30 days past due) commercial and industrial loans with respect to the unconditional sample mean of 1.64% (1.31%). Coefficient significance is high in the first two columns, and absent for charge-offs in column 3. Overall, evidence suggests SCBs are shifting towards slightly safer small business loans after local mobile infrastructure improvements.

Lastly, I test whether the mobile technology shock also pushes SCBs closer to market exit. The literature has long argued SCBs' relationship-based approach and their comparative advantage in small business lending have been fundamental in keeping them a viable enterprise after bank deregulation in the 80s and the 90s (DeYoung et al. (2004), Carter and McNulty (2005)). Having provided evidence of significant deposit outflows and reduced small business lending capabilities, I now check whether branch closures are rising as well.

[21] Results in this panel are based on shares of all commercial and industrial loans, not just those below $ 1 million, due to data availability.

For this purpose, I set up the following year-county-level identification strategy:

$$\textit{at least one net closing (opening)}_{c,t} = \alpha_c + \alpha_t + \beta_1 \textit{ spectrum expansions}_{c,t-1} + \gamma X_{c,t-1} + \epsilon_{c,t}, \tag{4}$$

where *at least one net closing*(*opening*)$_{c,t}$ is a dummy variable equal to 1 if county c has witnessed at least one net SCB branch closing (opening) in year t (i.e., if the number of SCB branches in county c and year t is smaller (larger) than the number the previous year), and *spectrum expansions*$_{c,t-1}$ capture mobile infrastructure improvements in county c and year $t-1$ in terms of 100s of MHz of new electromagnetic spectrum allotted to mobile network operators. α_c represent county fixed effects, α_t are year fixed effects, and $X_{c,t-1}$ is a set of lagged county-year demographic and end economic controls that include the number of branches, population, GDP, income per capita, employment rate, and the number of businesses.

Table 7 shows improvements in the local mobile infrastructure significantly increase the likelihood of SCB net branch closures and significantly decrease the likelihood of SCB net branch openings. According to columns 1 and 3, a significant increase in *sp. expansions*$_{c,t-1}$ of 100MHz—like the one that happened for many counties between 2015 and 2017—results in a 39.53% increase (50.75% decrease) in the likelihood of witnessing at least one a SCB net branch closure (opening) the year after with respect to the sample mean of 0.1475 (0.0938). In columns 2 and 4, I substitute *spectrum expansions*$_{c,t-1}$ with *sp. exp. above Ymedian*$_{c,t-1}$, a dummy variable equal to 1 if spectrum expansions by MNOs in county c are above the yearly median for the country in year $t-1$. This substitution captures the difference made by being on the greater side of mobile infrastructure improvements and ensures outliers do not drive the results in these county-level regressions. Simply being above the country median for mobile infrastructure improvements increases (decreases) the likelihood of witnessing at least one SCB net branch closure (opening) by 14.58% (25.05%). These magnitudes are very high, especially when considering that around 60% of SCBs have less than four branches total.[22] This mobile technology shock is threatening the survival of existing SCBs and discouraging their future development.

6 Consequences for small businesses

Having shown both decreased small business lending and increased bank branch closure rates for small community banks (henceforth SCBs) following improvements in the local mobile infrastructure, I proceed to investigate funding consequences for small businesses (section 6.1) and real effects (section 6.2).

6.1 Small business lending decrease

I start by quantifying the county-level decrease in small business lending by SCBs resulting from both the decreased lending from SCBs that are still operating (presented on a stand-alone basis through year-bank-level regressions in Table 6) and the loss of lending resulting from SCB branch closures (Table 7). I employ the following year-county-level regression:

$$ln(scb\, SBLs_{c,t}) = \alpha_c + \alpha_t + \beta_1\ spectrum\ expansions_{c,t-1} + \gamma X_{c,t-1} + \epsilon_{c,t}, \tag{5}$$

where $scb\ SBLs_{c,t}$ is the sum of the number/amount of all commercial and industrial loans below \$1 million on the balance sheets of SCBs having county c as their main county of operation in year t (Call Report data), and $spectrum\ expansions_{c,t-1}$ capture mobile infrastructure improvements in county c and year $t-1$ in terms of 100s of MHz of new electromagnetic spectrum allotted to mobile network operators. α_c represent county fixed effects,

[22] Untabulated analysis shows that whereas around 60 to 80% of the closing branches are acquired by larger banks every year, around 20 to 40% of them close permanently.

α_t are year fixed effects, and $X_{c,t-1}$ is a set of lagged county-year demographic and end economic controls that include the number of small community banks branches, population, GDP, income per capita, employment rate, and the number of small businesses.

Table 8, columns 1 and 3, highlight how a significant increase in $sp.\ expansions_{c,t-1}$—100MHz, like the one that happened for many counties between 2015 and 2017—results in an 11% decrease in the number of small business loans reported on the balance sheet of SCBs, and a 15.2% decrease in the amount. At the same time, columns 2 and 4 show simply being above the country median for mobile infrastructure improvements leads to a decrease in the number and amount of small business loans reported on the balance sheet of SCBs of around 3%. This effect is economically significant, not just from the point of view of SCBs, but for small businesses as well. Gopal and Schnabl (2020) estimate traditional commercial banks represent around 42.67% of overall small business lending, of which SCBs represent 22.46% (2016 data). According to these estimates, the 15.2% decrease in small business lending of SCBs I find would then result in a (42.67%*22.46%*15.2%=) 1.46% decrease in overall small business lending if no other player in the market takes action.

I thus consider larger, better-digitalized banks first. I analyze whether they increase their small business lending in response to the deposit inflows they witness following mobile infrastructure improvements (Table 5). In contrast to SCBs, these institutions are known for their transactional approach and for being less efficient at collecting soft information (Berger and Udell (2002), Cole et al. (2004), Berger et al. (2005), Bongini et al. (2007), Uchida et al. (2012)). For this reason, I do not expect them to pick up much of the small business lending now foregone by SCBs, even under the deposit increase.

I use Community Reinvestment Act (henceforth CRA) data for this part of the analysis. Up to this point, I have used Call Report data on commercial and industrial loans below $1 million to analyze small business lending. However, Call Report data are only available at the institution level, and I cannot geographically link them to the mobile infrastructure data with sufficient precision in the case of bigger banks. CRA reports are mandatory for banks with assets above the pre-determined \$1.1 billion/\$1.2 billion threshold. Hence, they cover all the non-community banks (large banks and big 4) in my sample and $\sim 75\%$ of the big community banks. For each of these banks, they detail small business loan originations by borrowers' location, which I can then link to the mobile infrastructure data. Furthermore, larger banks appear to frequently provide small business lending to borrowers located in counties where they do not maintain a physical presence. Therefore, I divide the CRA sample into small business loans to borrowers in counties where banks actively operate branches, and small business loans to borrowers in counties where banks do not operate a branch. Across these two subsamples, in Panel A and Panel B of Table 9 respectively, I estimate the following year-bank-county-level regression:

$$ln(lending\ amount_{b,c,t}) = \alpha_c + \alpha_t + \beta_1\ spectrum\ expansions_{c,t-1} + \gamma X_{c,t-1} + \alpha_c + \epsilon_{b,c,t}, \quad (6)$$

where $ln(lending\ amount_{b,c,t})$ is the natural logarithm of bank b small business lending in county c and year t, and $spectrum\ expansions_{c,t-1}$ capture mobile infrastructure improvements in county c and year $t-1$ in terms of 100s of MHz of new electromagnetic spectrum allotted to mobile network operators. Then, α_c represent county fixed effects, α_t are year fixed effects, and $X_{c,t-1}$ is a set of lagged county-year and bank-year controls. County-year controls include population, GDP, income per capita, employment rate, and number of small businesses. Bank-year controls include the number of bank b branches in the county, the ratio of nonperforming loans to assets, the ratio of net income to assets, a dummy variable taking the value of one if the branch(es) the bank operates in the county have been established more than 43 years before (sample median) to capture a long tradition of serving the community, the number of counties the bank operates in. In column 1 of Panel A, local small business lending by CRA banks does not appear to move with $spectrum\ expansions_{c,t-1}$ despite the larger deposit inflows these institutions get at the same time. The following columns show that results are robust to an increasingly heavier set of fixed effects, up to bank x year. I repeat the exercise on the subsample of loans to borrowers in counties where banks do not operate branches in Panel B. Here, all the coefficients on $\textit{spectrum expansions}_{c,t-1}$ are positive and statistically significant, suggesting that bigger banks increase small business lending in areas where they do not operate branches when there the mobile infrastructure improves. Furthermore, column 4 suggests that it is better-digitalized banks in particular that increase their small business lending where they do not operate branches (positive and significant coefficient on the interaction of $\textit{app available}_{b,t-1}$ with $\textit{spectrum expansions}_{c,t-1}$). Column 5 shows that this results holds when controlling for time-varying local economic conditions through county x year fixed effects as well. Overall, larger and better digitalized banks appear to increase their small business lending, but mainly in areas where they do not actively operate a branch.

I then consider FinTech firms. For this part of the analysis, I use small business lending data derived from UCC filings courtesy of Gopal and Schnabl (2020). They cover secured, non-real estate loan originations from 2010 to 2016. I have at my disposal just the simple count of said loans in each county each year originated by either banks or FinTech firms (separately). I therefore run the following year-county-level regression:

$$\Delta \; \# \; \textit{small business loans}_{c,t,t-1} = \alpha_c + \alpha_t + \beta_1 \; \textit{spectrum expansions}_{c,t-1} + \gamma X_{c,t-1} + \epsilon_{c,t}, \tag{7}$$

where $\Delta \; \textit{small business loans}_{c,t,t-1}$ is the number of small business loans granted (by either banks or FinTech) in county c at time t minus the corresponding number the previous year, and $\textit{spectrum expansions}_{c,t-1}$ capture mobile infrastructure improvements in county c and year $t-1$ in terms of 100s of MHz of new electromagnetic spectrum allotted to mobile network operators. α_c represent county fixed effects, α_t are year fixed effects, and $X_{c,t-1}$ is a set of lagged county-year demographic and end economic controls that include the number of bank branches, population, GDP, income per capita, employment rate, and the number of small businesses.

The first two columns of Table 10 show a decrease in overall small business lending from traditional commercial banks in UCC filings secured loan count data (negative and significant β_1 coefficient), suggesting that the digitalization of larger banks and higher capacity for small business lending at a distance do not overcome the drop in small community bank small business lending. Additionally, columns 3 and 4 provide evidence of FinTech firms partially making up for this decrease (positive and statistically significant coefficient β_1 across specifications, smaller in magnitude than the one capturing the decrease in bank loans in the previous two columns). However, the limited time span of UCC filings data (2010-2016) and the fact that they refer to the number of secured loans do not allow me to draw detailed conclusions on the precise extent to which FinTech firms can be considered an alternative to traditional commercial banks in small business lending. I can just generally conclude robust evidence exists of a drop in small business lending from SCBs following the mobile technology shock, which appears to be partially substituted away by FinTech firms and larger, better digitalized banks. From current estimates and previous tests on the level of loan riskiness carried by small community banks around technology shocks (section 5, Table 6, Panel C), certain small businesses that were able to receive lending before the shock might now be credit rationed. Therefore, I investigate potential real effects in the next section.

6.2 Real effects

In this section, I investigate the economic consequences of the SCB dynamics highlighted in the paper so far. In particular, I employ a specification that links small businesses' employment, wage, and count growth to mobile infrastructure improvements via the SCB channel:

$$\begin{aligned} \textit{growth variable}_{c,t} &= \alpha_c + \alpha_t + \beta_1 \textit{ spectrum expansions}_{c,t-1} \\ &+ \beta_2 \textit{ spectrum expansions}_{c,t-1} * \textit{share SCB deposits}_{c,2010} + \gamma X_{c,t-1} + \epsilon_{c,t}, \end{aligned} \tag{8}$$

where $\textit{growth variable}_{c,t}$ is either small business employment growth or wages growth based on the Census Bureau's Quarterly Workforce Indicators, or growth in the number of small businesses from the Census Bureau's County Business Patterns. $\textit{Spectrum expansions}_{c,t-1}$ capture mobile infrastructure improvements in county c and year $t-1$ in terms of 100s of MHz of new electromagnetic spectrum allotted to mobile network operators, and $\textit{share SCB deposits}_{c,2010}$ is SCBs' deposits over total county deposits in county c at the start of the sample (2010). α_c represents county fixed effects, α_t are year fixed effects, and $X_{c,t-1}$ is a set of lagged county-year demographic and end economic controls that include the number of bank branches, population, GDP, income per capita, and employment rate.

This specification aims to gauge real effects of the decrease in small business lending by SCBs after local mobile infrastructure improvements (section 6.1). The coefficient of interest is β_2, the interaction between the share of SCB deposits in the county at the start of the sample and local mobile infrastructure improvements.[23] It captures whether real consequences of mobile infrastructure improvements differ where SCBs had an important presence before the mobile technology shock. In particular, I would expect a negative and significant β_2 coefficient if FinTech firms are not fully able to substitute away the decrease in small business lending by SCBs.

[23] $\textit{Share SCB deposits}_{c,2010}$ is not present in the specification on its own, because it is absorbed by county fixed effects.

Table 11 presents results on small business employment growth in Panel A, small business wage growth in Panel B, and the growth rate of the number of small businesses in Panel C. Results are presented across columns by business size, defined as the number of employees in the business: columns 1 to 3 present estimations regarding small businesses with 1 to 19 employees, 20 to 59 employees, 50 to 499 employees, respectively. Additionally, column 4 in Panel C reports results for overall growth in county GDP.

Looking at the interaction coefficient alone (β_2 in equation 5 above), column 1 in Panel A shows how a significant improvement in mobile infrastructure—100 MHz—translates to a 0.3% decrease in employment by small businesses with 1 to 19 employees if small community banks served half of the depositors in the county in 2010 (the sample average prior to the mobile technology shock and financial services digitalization).[24] Column 1 in Panel B shows how a significant improvement in mobile infrastructure translates to a 0.26% decrease in wages for such businesses under the same condition.[25] Column 1 in Panel C shows how a significant improvement in mobile infrastructure translates to an 0.18% decrease in the number of such businesses under the same condition.[26] These effects are then counteracting positive and mostly significant coefficients on $\textit{spectrum expansions}_{c,t-1}$, whereby an important improvement in mobile infrastructure translates to a 0.24%, 0.56%, and 0.23% increase in employees, wages, and the number of businesses, respectively, for businesses with fewer than 20 employees. Nonetheless, they suggest that the economic growth that mobile infrastructure improvements would help achieve is partly neutralized by a lack of funding by SCBs following the same improvements. Magnitudes appear generally small, but note unconditional sample averages are 0.23%, 2.27%, and -0.14% for employees, wages, and businesses' growth, respectively, for businesses with less than 20 employees. Moreover, nearly half of the counties had SCBs covering more than 50% of overall deposits in 2010,

[24] 1*0.5*(-0.00593) = 0.003.
[25] 1*0.5*(-0.00522) = 0.0026.
[26] 1*0.5*(-0.00358) = 0.0018.

prior to digitalization. Similar patterns with slightly larger magnitudes appear in column 2 across panels regarding businesses with 20 to 49 employees. In contrast, larger businesses with 50 to 499 employees do not appear to respond to mobile infrastructure improvements.

Notably, a significant improvement in mobile infrastructure is associated with a 3.91% increase in county GDP, then counteracted by a 1.78% decrease if SCBs had 50% of the deposits in the county prior to digitalization (column 4 of Panel C). Overall, evidence suggests a diffused presence of SCBs prior to digitalization leads to lower economic gains from it. This finding indirectly confirms the lack of full substitutability between the small business lending operated by SCBs—that is drying up under deposit outflows—and the one operated by FinTech firms.

7 Robustness

I conduct a series of robustness tests to support the findings in the paper. First, I make sure my results are consistent across different geographies. Second, I set up event studies around significant improvements in the local mobile infrastructure to confirm previous findings regarding small community banks' (henceforth SCBs) response to digitalization. Third, I try my best to address concerns of omitted variable bias.

7.1 Geographical distribution of effects

One primary concern in the analysis is the geographical distribution of the highlighted effects. SCBs have a weaker presence in urban areas, where cell phone reception might also be better. Therefore, I might be picking up urban versus rural evolutionary patterns rather than the effect of mobile technology adoption. Against this argument, my measure of mobile infrastructure improvements does not present significant differences across rural and urban geographies (see Figure 1 for reference). However, it captures the ex-ante intention to use more electromagnetic spectrum for smoother mobile communications with no guarantee of the actual implementation. For such reasons, in Appendix B, I replicate the analysis within three different subsamples: counties belonging to metropolitan statistical areas, counties belonging to micropolitan statistical areas, and the remaining counties (which I label rural).[27]

Table B.1 replicates bank competition estimates: Panel A on deposit flows, Panel B on deposit pricing. Results across subsamples (columns 2 to 4) are consistent with the full-sample estimates reported in column 1 and previously presented in the paper. The only difference is the lack of significance and a smaller magnitude of $\textit{spectrum expansion}_{c,t-1}$ regarding county deposits in micropolitan areas, suggesting less to no outflows from SCBs in such counties. As much in metropolitan areas as in rural ones, there however appear to be significant outflows of deposits from SCBs following improvements in local mobile infrastructure. Furthermore, SCBs exploit their remaining customers through higher pricing, whereas bigger, better-digitalized banks increase their rates to appeal to potential new customers.

Table B.2 presents estimates on SCBs' asset side of the balance sheet at the county-year level. Each panel represents a different (sub)sample, whereas the different columns have the different lending types as outcome variables. Here, the overall sample result of a decrease in SCB small business lending following mobile infrastructure improvements seems to be mainly driven by metropolitan areas. The reason is that SCB small business lending is less important in rural areas, where more small farm lending occurs instead. In the main specification, loans to small farms fall in the residual category of $ln(\textit{other loans}\ _{b,t})$, where they are pooled with other loan types. In the last column of Panel D, I report loans to small farms alone and show how they drop significantly following improvements in local mobile infrastructure in rural areas—at an even faster rate than small business loans in metropolitan

[27]"The United States Office of Management and Budget (OMB) delineates metropolitan and micropolitan statistical areas. [...] Each metropolitan statistical area must have at least one urbanized area of 50,000 or more inhabitants. Each micropolitan statistical area must have at least one urban cluster of at least 10,000 but less than 50,000 population." - Census Bureau.

statistical areas. Micropolitan areas do not present strong patterns, although they have the fewest observations entering the estimation. Still, the drop in SCBs' loans to small economic enterprises appears in both metropolitan and rural areas.

Untabulated analysis replicates estimates on whether bigger and better-digitalized banks (CRA filers) increase their small business lending after mobile infrastructure improvements. The result in the main analysis shows these banks' local small business lending does not respond to mobile infrastructure improvements. The result is confirmed within metropolitan, micropolitan, and rural areas.

Table B.3 replicates results on whether FinTech firms are making up for the decrease in small business/farm lending highlighted in the previous tables. The independent variable is the count of secure, non-real estate loans in first difference, based on data from Gopal and Schnabl (2020). The substitution effect between FinTech firms and SCBs highlighted in section 6.1 appears to come almost exclusively from metropolitan areas. No substitution effect occurs in micropolitan areas, and a minimal one occurs in rural areas. This finding highlights a higher propensity to switch to FinTech firms in urban areas, likely corresponding with a younger and more educated population. However, this analysis is still limited by the fact that the data cover just the count of secured non-real estate loans from 2010 to 2016.

Lastly, Table B.4 replicates the analysis on the real effects of mobile infrastructure improvements via the SCB channel across subsamples. Therefore, the coefficient of interest is the interaction between *spectrum expansions* $_{t-1}$ and the share of SCB deposits in the county prior to digitalization (2010). It is negative and grows in absolute magnitude when progressing from urban to rural areas. This pattern is in line with the previous table showing little substitution with FinTech firms in micropolitan and rural areas.

Overall, most of the results exposed in previous sections are consistent across geographies. However, substitution with FinTech firms seems to be mainly concentrated in metropolitan areas, with digitally-spurred economic growth being more jeopardized in rural ones.

7.2 Event study analysis

In Appendix C, I conduct an event-study analysis around important improvements in mobile infrastructure. I consider an event window from two years before the event to two years after. I define an event as the county-year observation corresponding to the highest year-on-year % increase in spectrum expansions above 60% for the county. For each of said event observations, I then single out five untreated (i.e., not belonging to any event window) nearest neighbors in the year prior to the one of the event observation based on population, GDP, and income per capita. I then exclude the nearest neighbors that witnessed moderately high increases in spectrum expansions around the event. If more than one nearest neighbor remains, I pick the one with the lowest increase in spectrum expansions in the year of the event. Because spectrum expansions display an increasing trend everywhere over time (see Table 1 and Figure 1 for reference), this matching procedure is critical in pairing high increases (the treatments) to very low ones (the best control options available). Across the analysis, I therefore do not expect the total absence of patterns in the control group, but I still expect stronger effects in the treatment group.

First, I test how SCB branch closure rates respond to said important improvements in mobile infrastructure through the following specification:

$$\textit{at least one net closing}_{\,c,t} = \alpha_c + \alpha_t + \alpha_k + \beta_1\, Treated_c * Post_t + \gamma X_{c,t-1} + \epsilon_{k,c,t}, \qquad (9)$$

where $\textit{at least one net closing}_{\,c,t}$ is a dummy variable equal to 1 if county c has witnessed at least one net SCB branch closing in year t, $Treated_c$ is a dummy variable equal to 1 if the county witnessed a year-on-year percentage increase of at least 60% and to 0 if it belongs to the control group, $Post_t$ is a dummy variable equal to 1 for the treated and their matched controls in the two years after the event, and α_k represent cohort fixed effects (one for each pair of treated county with its control).[28] Table C.1 reports estimates of this regression. The coefficient of interest β_1 is positive and significant across specifications, meaning higher rates of SCB branch closures in treated counties after the event ($\sim +30\%$ increase with respect to the unconditional sample average). Figure C.1 reports changes in interaction coefficients over the event years with respect to the year prior the event. The parallel trends assumption seems satisfied, and the year after the event presents the only positive coefficient significantly different from zero, for treated counties alone. Even in this setting, SCB branch closures appear to be negatively affected by mobile infrastructure improvements.

Second, I test whether SCBs decrease their small business lending following important improvements in the local mobile infrastructure. I apply the same procedure just outlined, substituting $high\ decrease\ in\ SCB\ small\ business\ lending_{\ c,t}$ as the new outcome variable. $High\ decrease\ in\ SCB\ small\ business\ lending_{\ c,t}$ is a dummy variable equal to 1 if SCB small business lending dropped by at least 60% in year t and county c with respect to the previous year. Table C.2 reports estimation results, with the coefficient of interest (the interaction of $Treated_c$ and $Post_t$) positive and statistically significant across specifications, meaning a greater likelihood of high small business lending decreases for SCBs in treated counties after the event ($\sim +72\%$ increase with respect to the unconditional sample average). According to Figure C.2, the parallel trends assumption seems satisfied, and the year after the event presents the only positive coefficient significantly different from zero, for treated counties alone. SCBs appear more likely to significantly reduce small business lending after large mobile infrastructure improvements in this setting as well.

[28] $Treated_c$ and $Post_t$ do not enter the equation on their own, because they are absorbed by county and time fixed effects, respectively.

7.3 Instrumental variable analysis

In this last section, I address the concern that a third element could be driving both mobile infrastructure improvements and banking patterns. This scenario does not seem likely, since the progressive addition of controls and fixed effects in my specifications barely affect the magnitude and significance of coefficients or the R^2s throughout the analysis. Furthermore, my mobile infrastructure improvements data come from licenses that the Federal Communication Commission mainly assigns through centralized auctions that span the entirety of the United States at once.

Nonetheless, previous papers that have used 2G and 3G mobile coverage proprietary data in their analysis frequently address this concern by instrumenting mobile coverage with the likelihood of lightning strikes (Manacorda and Tesei (2020), Guriev et al. (2021), Jiang et al. (2022)). Frequent lightning strikes from cloud to ground damage mobile infrastructure and cellular signal transmission, making providing mobile communication services more costly (Andersen et al. (2012)). As such, they should also slow down mobile infrastructure improvements (relevance condition, proved in the first stage). Regarding the exclusion condition, these studies have assumed local economic conditions are not related to weather conditions. In the current study, it would be safe to assume that bank decisions should not rely on weather conditions either if these conditions are not affecting the local economy. The only caveat in adopting this methodology in this paper's setting is that I capture both 3G and 4G expansions through my mobile infrastructure data. Whereas 3G expansions entailed the rollout of new towers, 4G entails both rolling out new towers and placing new antennas on existing ones. Lightning strikes would not slow down antenna placements on existing towers, but I cannot distinguish when this is the case in my data. The instrument will therefore be weaker and likely cause less precise estimates than in previous literature.

I rely on National Lightning Detection Network data for the number of cloud-to-ground lightning strikes in each county each year. Following previous literature, I construct a dummy variable equal to 1 if the county's average frequency of lightning strikes from 2010 to 2019 is above the sample median. Because this measure is time invariant, I reduce all other variables in the IV regression to their average across 2015 to 2018—the peak of mobile spectrum expansions in my sample.

Table D.1 replicates estimates for SCB branch closures (Table 7 in the main analysis) with *spectrum expansions*$_c$ instrumented by *above med. lightning strikes*$_c$. Column 1 reports first-stage estimates, with *above med. lightning strikes*$_c$ being a negative and significant predictor of *spectrum expansions*$_c$. In the second stage, predicted values for *spectrum expansions*$_c$ report positive (negative) and significant coefficients in relation to the likelihood of SCBs' net branch closure (opening). This estimate confirms results in the previous analysis, albeit with much larger magnitudes, likely due to instrument weakness.

Table D.2 replicates estimates for SCB small business lending (Table 8 in the main analysis) with *spectrum expansions*$_c$ instrumented by *above med. lightning strikes*$_c$. Column 1 reports first-stage estimates, with *above med. lightning strikes*$_c$ again being a negative and significant predictor for *spectrum expansions*$_c$. In the second stage, predicted values for *spectrum expansions*$_c$ report a negative and significant coefficient relative to small business lending (commercial and industrial loans below $1 million). This estimate confirms results in previous analysis, albeit with abnormal magnitudes and R-squares, likely due to instrument weakness.

Overall, IV estimates confirm previous findings in the sign and significance of the coefficients of interest. However, magnitudes appear larger, potentially due to the weak instrumentation mentioned above.

8 Conclusion

Previous literature has highlighted the increasing competition posed by FinTech firms' fully digitalized financial services to the traditional commercial banking sector. However, it has ignored that competition within the traditional commercial banking sector has also changed due to the varying degrees to which depository institutions have been able to digitalize their own services.

In this paper, I show banks slow to adopt mobile technology, namely, small community banks, lose significant amounts of deposits to larger, better-digitalized banks following mobile infrastructure improvements. At the same time, they opt to charge remaining customers higher prices. Further, these institutions have always been highly reliant on the synergies with deposits to maintain their renowned competitiveness in the small business lending market. These technology-spurred deposit outflows are now negatively affecting their capacity for small business lending and leading to branch closures. Bigger banks do not increase their small business lending enough in return, and together with FinTech firms they seem to be able to substitute for small community banks in this market only partially. The result is fewer economic gains from digitalization in those geographies where small community banks had a strong presence prior to its advent.

Besides highlighting unprecedented competition dynamics, the findings in this paper also provide important insights into the future of relationship lending and the sensitivity of the traditional commercial bank business model to technological shocks.

The introduction of mobile technology has pushed small community banks closer to market exit. Furthermore, part of their relationship lending is now disappearing with little replacement. Nevertheless, I show big community banks—depository institutions with assets above $1 billion yet still focused on the local community—fare the technology shock well and continue undisturbed in their significant small business lending activities. Economies of scale seem to exist within the community bank business model that could help relationship lending remain a possibility for small businesses in the future.

Additionally, my findings highlight how the mobile technology shock has deprived small community banks of some of the synergies between deposit-taking and lending that lie at the core of their business model. Emerging FinTech firms are not reliant on these synergies by construction—they usually do not take deposits and specialize in providing one specific financial service. Therefore, it becomes an open question whether the traditional bank business model will withstand further digital progress.

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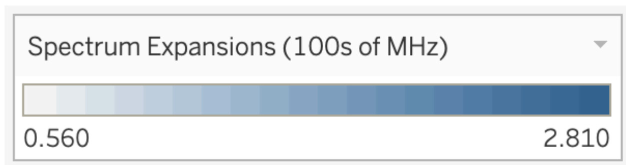
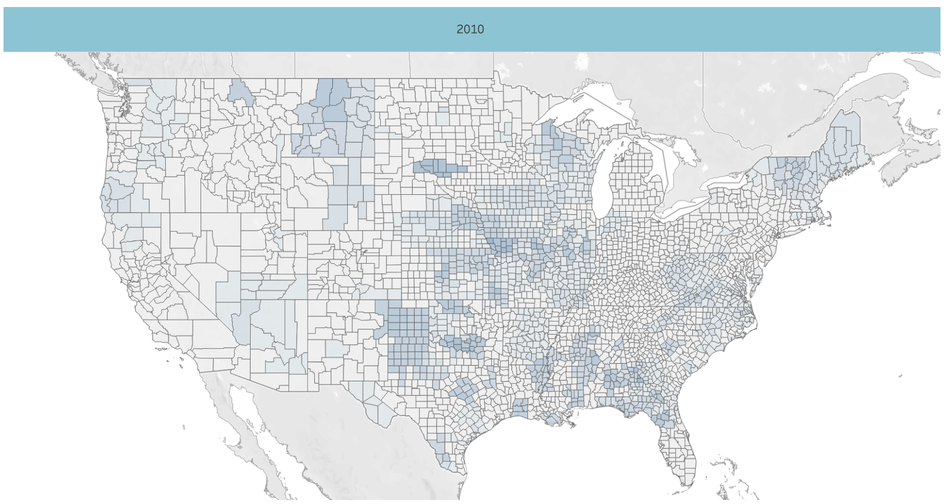
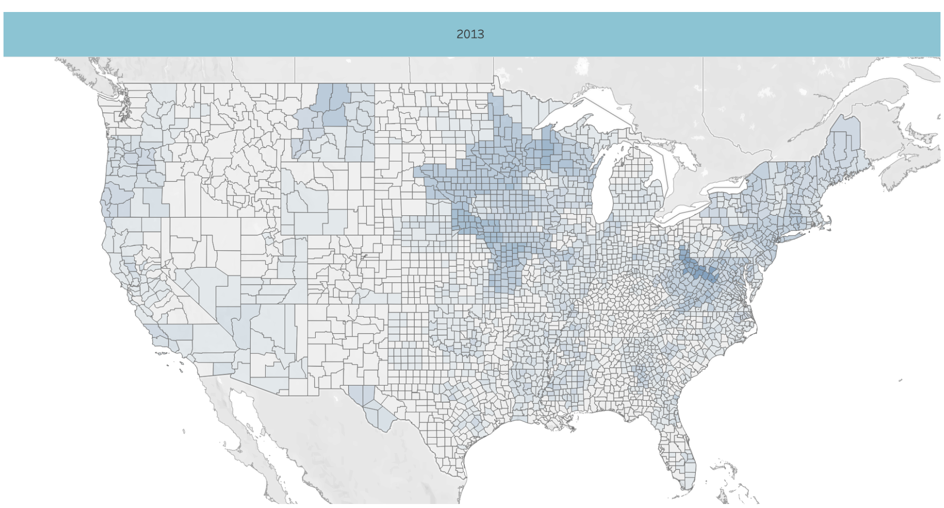
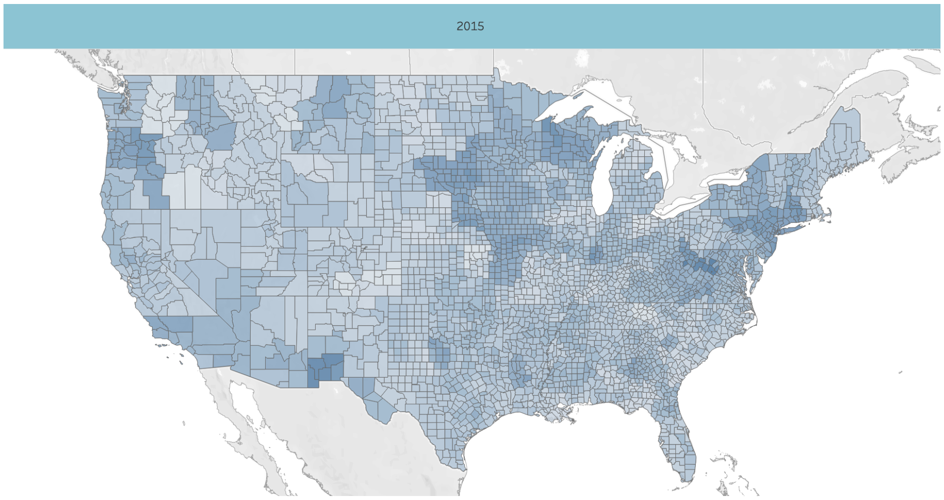
Figure 1: **Spectrum holdings over time**

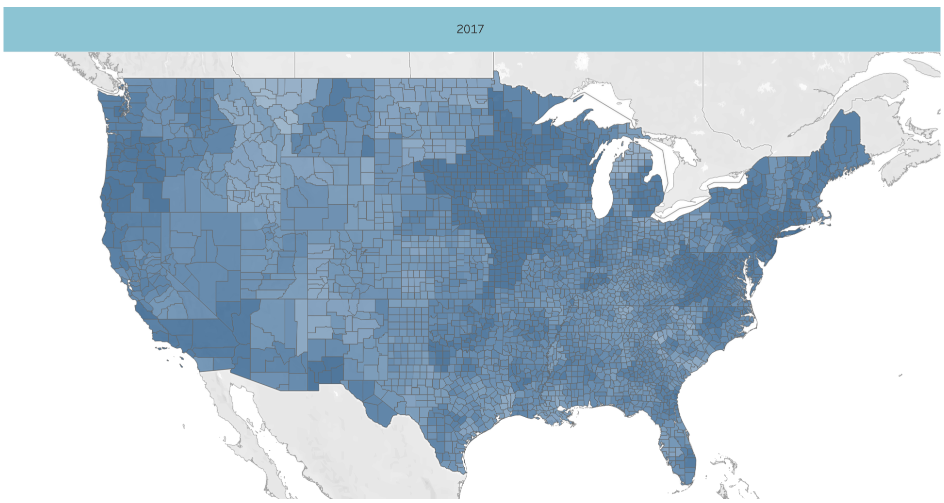
Description: This figure maps Mobile Network Operators' spectrum expansion across U.S. counties by year.








2015


2017

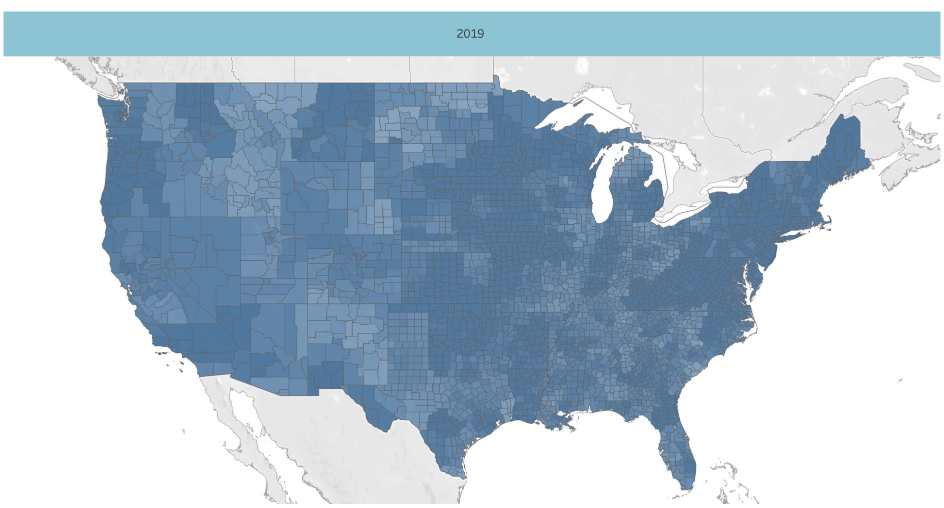

2019

Figure 2: **Mobile banking adoption rates over time**

Description: This figure plots the % of depository institutions with a mobile banking app within each bank type as defined in section 4.

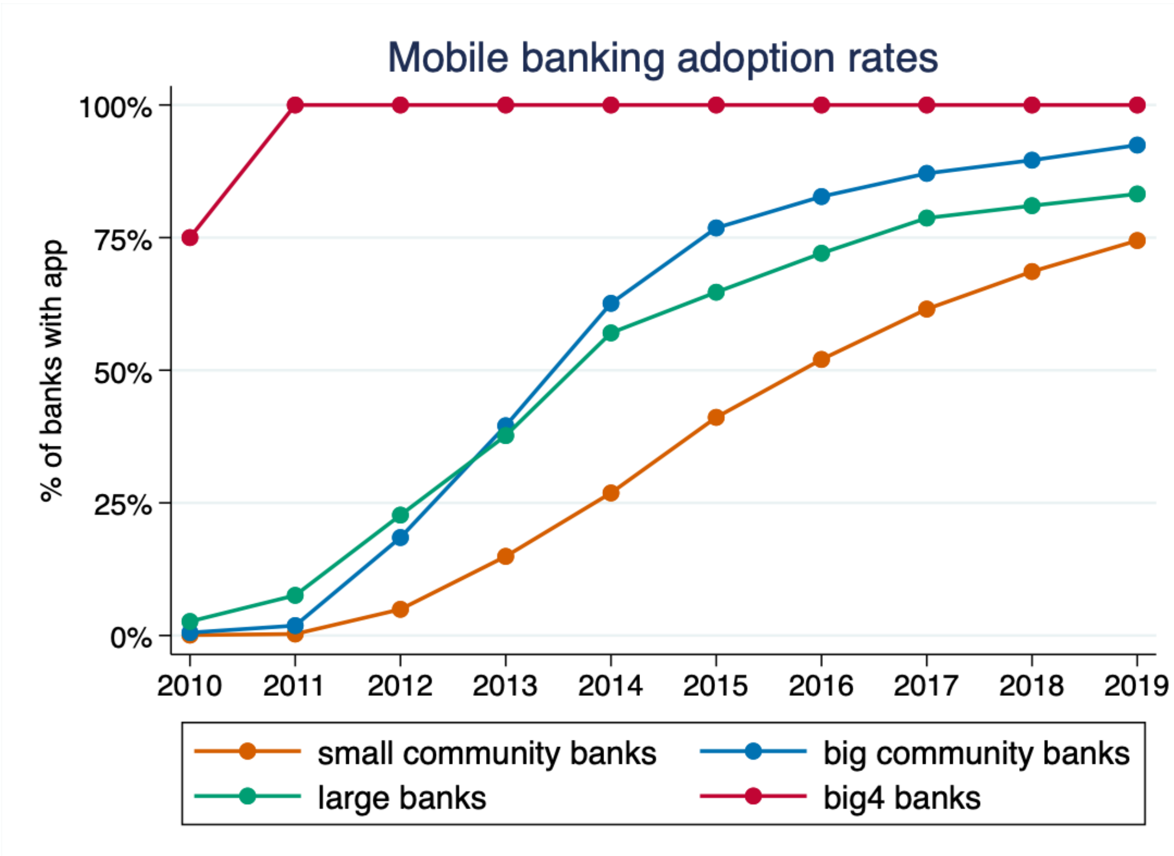


Table 1: **Spectrum Expansions (in 100s of MHz)**

Description: This table presents summary statistics for Mobile Network Operators' spectrum expansion across U.S. counties by year.

year	mean	st. dev.	min	5^{th} p.	25^{th} p.	50^{th} p.	75^{th} p.	95^{th} p.	max
2010	0.68	0.18	0.13	0.52	0.56	0.63	0.76	1.05	1.53
2011	0.72	0.18	0.36	0.56	0.56	0.66	0.80	1.11	1.63
2012	0.69	0.15	0.36	0.56	0.56	0.66	0.76	0.97	1.44
2013	0.78	0.22	0.38	0.56	0.58	0.74	0.88	1.17	1.85
2014	0.92	0.24	0.49	0.67	0.77	0.88	1.03	1.40	1.95
2015	1.32	0.26	0.81	0.99	1.12	1.28	1.49	1.83	2.41
2016	1.56	0.29	0.92	1.24	1.35	1.51	1.67	2.17	3.02
2017	2.35	0.36	0.40	1.85	2.13	2.31	2.56	3.03	3.63
2018	2.49	0.36	0.50	1.97	2.25	2.44	2.68	3.15	4.06
2019	2.63	0.36	0.70	2.09	2.39	2.60	2.82	3.30	4.18
total	1.41	0.80	0.13	0.56	0.69	1.16	2.17	2.83	4.18

Table 2: **The Universe of Depository Institutions**

Description: This table presents summary statistics for the universe of U.S. depository institutions in 2010 (begginning of sample, upper panel) and 2019 (end of sample, lower panel). Data are presented for each bank type of the framework employed in the analysis and presented in section 4.

	# institutions	avg. # branches	avg. deposits	avg. # branches per county	avg. deposits per county	avg. # of counties
June 2010						
community banks	6,277	4.04	USD 157 mill.	2.08	USD 89 mill.	1.98
big community banks	557	18.54	USD 1.12 bill.	4.37	USD 336 mill.	5.38
large banks	227	162.98	USD 12.55 bill.	3.82	USD 1.82 bill.	35.07
big4 banks	4	4,729	USD 608.96 bill.	8.87	USD 1.34 bill.	556.75
full sample	7,153	12.97	USD 976.05 mill.	2.32	USD 164.88 mill.	3.60
June 2019						
community banks	4,442	4.34	USD 210 mill.	1.99	USD 107 mill.	2.29
big community banks	556	19.59	USD 1.72 bill.	3.93	USD 468 mill.	6.37
large banks	298	136.14	USD 21.35 bill.	3.13	USD 4.29 bill.	35.47
big4 banks	4	3,910.5	USD 1.13 trill.	9.94	USD 4.28 bill.	456.25
full sample	5,351	16.30	USD 2.41 bill.	2.26	USD 382.46 mill.	4.89

Table 3: **Technology-driven Competition on Deposits**

Description: This table presents results on technology-driven competition on deposits. The dependent variable is the natural logarithm of bank b deposits in county c and year t in Panel A, deposit spread of bank b in county c and year t (quarterly Fed Funds Rate minus bank b's county average of Money Market 25K rates at rate-setting branches) in Panel B. Across specifications, *sp. expansions* $_{c,t-1}$ captures MNOs spectrum expansions in county c and year $t-1$ and *app available* $_{b,t-1}$ is a dummy equal to 1 if bank b offers a banking app in year $t-1$. Standard errors are clustered at county level; ***, **, * denote 1%, 5%, and 10% statistical significance; - denotes a coefficient absorbed by fixed effects..

Panel A: Deposit Flows

	ln(deposits $_{b,c,t}$)			
	(1)	(2)	(3)	(4)
sp. expansions$_{c,t-1}$	-0.0592***	-0.0707***	-	-
	(0.014)	(0.014)		
app available$_{b,t-1}$	-0.134***	-0.216***	-0.246***	-0.0329*
	(0.021)	(0.022)	(0.025)	(0.019)
app available$_{b,t-1}$ × sp. expansions$_{c,t-1}$	0.148***	0.144***	0.167***	
	(0.011)	(0.012)	(0.013)	
app available$_{b,t-1}$ × placebo sp. expansions$_{c,t-1}$				0.00903
				(0.0088)
ln(population$_{c,t-1}$)	0.472***	0.158	-	-
	(0.11)	(0.11)		
# branches$_{c,t-1}$	0.0740***	0.0710***	0.0707***	0.0707***
	(0.012)	(0.012)	(0.012)	(0.012)
ln(businesses$_{c,t-1}$)	0.328***	0.317***	-	-
	(0.073)	(0.076)		
employment rate$_{c,t-1}$	-0.0978	-0.191*	-	-
	(0.10)	(0.10)		
ln(personal income pc$_{c,t-1}$)	0.232***	0.171***	-	-
	(0.043)	(0.042)		
ln(county GDP$_{c,t-1}$)	0.100***	0.123***	-	-
	(0.021)	(0.021)		
NPLs over assets$_{b,t-1}$	-1.623**	-1.845**	-2.681***	-2.742***
	(0.82)	(0.82)	(0.87)	(0.88)
net income over assets$_{b,t-1}$	-6.248*	-6.084	-6.218	-6.292
	(3.78)	(3.73)	(3.86)	(3.89)
legacy in county$_{b,c,t-1}$	1.129***	1.113***	1.120***	1.120***
	(0.040)	(0.038)	(0.038)	(0.038)
# counties covered$_{b,t-1}$	-0.0000489	-0.00109***	-0.00110***	-0.00113***
	(0.000052)	(0.000055)	(0.000055)	(0.000056)
county FE	x	x		
year FE	x			
county x year FE			x	x
bank type x year FE		x	x	x
observations	252,517	252,517	251,198	251,072
R-squared	0.484	0.501	0.509	0.508
Within R2	0.350	0.324	0.326	0.325

Panel B: Deposit Pricing

	deposit spread $\%_{b,c,t}$			
	(1)	(2)	(3)	(4)
sp. expansion$_{c,t-1}$	-0.0116***	-0.00771***	-	-
	(0.0021)	(0.0021)		
app available$_{b,t-1}$	-0.00595***	0.00466**	-0.000289	0.00838***
	(0.0021)	(0.0022)	(0.0029)	(0.0025)
app available$_{b,t-1}$ $\times$ sp. expansion$_{c,t-1}$	0.00589***	0.000188	0.00593***	
	(0.0013)	(0.0014)	(0.0018)	
app available$_{b,t-1}$ $\times$ placebo sp. expansions$_{c,t-1}$				-0.000225
				(0.0017)
# county branches$_{b,c,t-1}$	0.00121***	0.000927***	0.000905***	0.000903***
	(0.000043)	(0.000044)	(0.000047)	(0.000047)
ln(population$_{c,t-1}$)	-0.0582***	0.0196	-	-
	(0.019)	(0.019)		
ln(county GDP$_{c,t-1}$)	0.0128**	0.00134	-	-
	(0.0052)	(0.0051)		
ln(businesses$_{c,t-1}$)	-0.170***	-0.194***	-	-
	(0.014)	(0.014)		
ln(personal income pc$_{c,t-1}$)	0.0664***	0.0481***	-	-
	(0.0096)	(0.0095)		
employment rate$_{c,t-1}$	-0.0624***	-0.0124	-	-
	(0.024)	(0.024)		
NPLs over assets$_{b,t-1}$	-1.412***	-1.573***	-1.714***	-1.718***
	(0.038)	(0.037)	(0.047)	(0.047)
net income over assets$_{b,t-1}$	-0.522***	-0.784***	-1.068***	-1.070***
	(0.074)	(0.073)	(0.088)	(0.088)
legacy in county$_{b,c,t-1}$	0.0320***	0.0271***	0.0261***	0.0261***
	(0.0010)	(0.0010)	(0.0011)	(0.0011)
# counties covered$_{b,t-1}$	0.000234***	0.000161***	0.000154***	0.000153***
	(0.0000030)	(0.0000040)	(0.0000045)	(0.0000044)
county FE	x	x		
quarter	x			
bank type x quarter FE		x	x	x
county x quarter x FE			x	x
observations	240,635	240,635	207,877	207,877
R-squared	0.951	0.953	0.960	0.960
Within R2	0.0606	0.0244	0.0278	0.0277

Table 4: **App adoption**

Description: This table presents results of models for the timing of mobile banking technology adoption. Panel A provides *hazard ratios* from a parametric hazard model run across all banks where the end-event is the adoption of the app. The model is calibrated on a Weibull survival distribution to take into account that the likelihood of getting an app increases over time as the service becomes more and more popular. Hazard ratios above one represent quicker app adoption, below one slower app adoption. Panel B presents linear probability models where the dependent variables are % *branches providing* $app_{c,t}$ in columns 1 and 2 and % *deposits with* $app_{c,t}$ in columns 3 and 4. % *branches providing* $app_{c,t}$ measures the percentage of county branches belonging to banks that provide mobile banking apps in county c and year t, % *deposits with* $app_{c,t}$ measures the percentage of county deposits held at banks that provide mobile banking apps in county c and year t. Panel C repeats the linear regression model across subsamples. The dependent variable in column1 is the percentage of small community bank branches providing an app relative to total small community bank branches. The dependent variable in column 2 is the percentage of big community bank branches providing an app relative to total big community bank branches. The dependent variable in column 3 is the percentage of non-community bank branches providing an app relative to total non-community bank branches.

Panel A: Hazard model

	app available$_{b,t}$
	(1)
big community bank$_{b,t-1}$	2.3452***
	(0.1195)
large bank$_{b,t-1}$	1.4777***
	(0.1138)
deposit-weighted avg sp. expansions$_{b,t-1}$	0.3221***
	(0.0122)
deposit-weighted avg % of pop. 65y and older$_{b,t-1}$	0.8359***
	(0.0313)
deposit-weighted avg % of pop. w/higher education$_{b,t-1}$	1.1474***
	(0.0259)
NPLs over assets$_{b,t-1}$	0.0150
	(0.0468)
net income over assets$_{b,t-1}$	0.2220
	(0.2705)
observations	38,482

Panel B: Linear regression models

	% branches providing app$_{c,t}$		% deposits with app$_{c,t}$	
	(1)	(2)	(3)	(4)
sp. expansions$_{c,t-1}$	-0.0298***	-0.0261***	-0.0254***	-0.0214**
	(0.0090)	(0.0085)	(0.0097)	(0.0092)
% pop. 65y and older$_{c,2010}$	-0.595***	-0.165***	-0.666***	-0.204***
	(0.057)	(0.056)	(0.061)	(0.060)
% pop. w/higher education$_{c,2010}$	0.501***	0.179***	0.578***	0.232***
	(0.036)	(0.036)	(0.044)	(0.043)
I(big comm. bank branches$_{c,t}$)		0.0407***		0.0408***
		(0.0048)		(0.0052)
I(large bank branches$_{c,t}$)		0.0767***		0.0836***
		(0.0080)		(0.0085)
I(big4 bank branches$_{c,t}$)		0.0962***		0.105***
		(0.0062)		(0.0069)
state FE	x	x	x	x
year FE	x	x	x	x
observations	31,612	31,612	31,612	31,612
R-squared	0.644	0.668	0.610	0.636
Within R2	0.0476	0.112	0.0518	0.115

Panel C: app adoption and spectrum expansions

	% branches providing app$_{c,t}$		
	(1)	(2)	(3)
	small community banks	big community banks	non-community banks
sp. expansions$_{c,t-1}$	-0.0273**	-0.0143	0.000758
	(0.012)	(0.014)	(0.011)
pop. 65y and older$_{c,2010}$	-0.173**	-0.0259	-0.299***
	(0.068)	(0.087)	(0.073)
pop. w/higher education$_{c,2010}$	0.180***	0.0437	0.301***
	(0.047)	(0.054)	(0.044)
state FE	x	x	x
year FE	x	x	x
observations	28,349	16,278	25,191
R-squared	0.592	0.632	0.496

Table 5: **Technology-driven Competition on Deposits, by Bank Type**

Description: This table presents results on technology-driven competition on deposit when considering considering *bank type* (*small community banks*, *big community banks*, *large banks*, *big4 banks*) as a proxy for mobile technology adoption and quality. The dependent variable is the natural logarithm of bank b deposits in county c and year t in Panel A, deposit spread of bank b in county c and year t (quarterly Fed Funds Rate minus bank b's county average of Money Market 25K rates at rate-setting branches) in Panel B. Across specifications, $sp.\ expansions_{c,t-1}$ captures MNOs spectrum expansions in county c and year $t-1$. Standard errors are clustered at county level; ***, **, *, $^{+}$ denote 1%, 5%, 10%, 15% statistical significance; - denotes a coefficient absorbed by fixed effects.

Panel A: Deposit Flows

	ln(deposits $_{b,c,t}$)			
	(1)	(2)	(3)	(4)
sp. expansions$_{c,t-1}$	-0.0483***	-0.0683**	-	-
	(0.013)	(0.029)		
big community bank$_{b,t}$	0.373***	-	-	-
	(0.033)			
large bank$_{b,t}$	0.130***	-	-	-
	(0.032)			
big4 bank$_{b,t}$	0.971***	-	-	-
	(0.051)			
big comm. bank$_{b,t}$ × sp. expansions$_{c,t-1}$	0.0386***	-0.0366	-0.0462	
	(0.013)	(0.057)	(0.062)	
large bank$_{b,t}$ × sp. expansions$_{c,t-1}$	0.141***	0.222***	0.229***	
	(0.0097)	(0.057)	(0.063)	
big4 bank$_{b,t}$ × sp. expansions$_{c,t-1}$	0.192***	0.163+	0.174+	
	(0.016)	(0.099)	(0.11)	
big comm. bank$_{b,t}$ × placebo sp. expansions$_{c,t-1}$				0.00197
				(0.011)
large bank$_{b,t}$ × placebo sp. expansions$_{c,t-1}$				0.0246***
				(0.0084)
big4 bank$_{b,t}$ × placebo sp. expansions$_{c,t-1}$				0.0187
				(0.014)
ln(population$_{c,t-1}$)	0.219**	0.166	-	-
	(0.11)	(0.11)		
# branches$_{c,t-1}$	0.0710***	0.0709***	0.0706***	0.0706***
	(0.012)	(0.012)	(0.012)	(0.012)
ln(businesses$_{c,t-1}$)	0.278***	0.302***	-	-
	(0.075)	(0.075)		
employment rate$_{c,t-1}$	-0.188*	-0.187*	-	-
	(0.10)	(0.10)		
ln(personal income pc$_{c,t-1}$)	0.150***	0.164***	-	-
	(0.042)	(0.042)		
ln(county GDP$_{c,t-1}$)	0.117***	0.123***	-	-
	(0.021)	(0.021)		
NPLs over assets$_{b,t-1}$	-1.802**	-1.928**	-2.773***	-2.731***
	(0.84)	(0.83)	(0.88)	(0.88)
net income over assets$_{b,t-1}$	-6.244	-6.158	-6.303	-6.298
	(3.81)	(3.76)	(3.90)	(3.90)
legacy in county$_{b,c,t-1}$	1.113***	1.114***	1.121***	1.120***
	(0.038)	(0.038)	(0.038)	(0.038)
# counties covered$_{b,t-1}$	-0.00108***	-0.00112***	-0.00114***	-0.00114***
	(0.000056)	(0.000057)	(0.000057)	(0.000057)
county FE	x	x		
year FE	x			
county x year FE			x	x
bank type x year FE		x	x	x
observations	252,517	252,517	251,198	251,072
R-squared	0.500	0.501	0.509	0.508
Within R2	0.371	0.323	0.326	0.325

Panel B: Deposit Pricing

	deposit spread$_{b,c,t}$			
	(1)	(2)	(3)	(4)
sp. expansion$_{c,t-1}$	-0.00715***	-0.0149***	-	-
	(0.0020)	(0.0023)		
big comm. bank$_{b,t}$	0.0570***	-	-	-
	(0.0025)			
large bank$_{b,t}$	0.0882***	-	-	-
	(0.0020)			
big 4 bank$_{b,t}$	0.0691***	-	-	-
	(0.0054)			
big comm. bank$_{b,t}$ × sp. expansion$_{c,t-1}$	-0.00370**	0.0448***	0.0349***	
	(0.0016)	(0.0047)	(0.0059)	
large bank$_{b,t}$ × sp. expansion$_{c,t-1}$	-0.00895***	0.00158	0.0212***	
	(0.0012)	(0.0039)	(0.0049)	
big 4 bank$_{b,t}$ × sp. expansion$_{c,t-1}$	0.0143***	0.0664***	0.0718***	
	(0.0035)	(0.010)	(0.012)	
big comm. bank$_{b,t}$ × placebo sp. expansions$_{c,t-1}$				-0.000383
				(0.0021)
large bank$_{b,t}$ × placebo sp. expansions$_{c,t-1}$				0.00206
				(0.0016)
big 4 bank$_{b,t}$ × placebo sp. expansions$_{c,t-1}$				0.00625
				(0.0038)
# county branches$_{b,c,t-1}$	0.000893***	0.000946***	0.000929***	0.000915***
	(0.000044)	(0.000044)	(0.000047)	(0.000047)
ln(population$_{c,t-1}$)	-0.0808***	0.0275	-	-
	(0.019)	(0.019)		
ln(county GDP$_{c,t-1}$)	0.0129**	0.000870	-	-
	(0.0051)	(0.0051)		
ln(businesses$_{c,t-1}$)	-0.169***	-0.195***	-	-
	(0.014)	(0.014)		
ln(personal income pc$_{c,t-1}$)	0.0697***	0.0498***	-	-
	(0.0096)	(0.0095)		
employment rate$_{c,t-1}$	-0.0572**	-0.0104	-	-
	(0.024)	(0.024)		
NPLs over assets$_{b,t-1}$	-1.503***	-1.577***	-1.726***	-1.724***
	(0.037)	(0.037)	(0.047)	(0.047)
net income over assets$_{b,t-1}$	-0.926***	-0.784***	-1.066***	-1.068***
	(0.074)	(0.073)	(0.088)	(0.088)
legacy in county$_{b,c,t-1}$	0.0283***	0.0272***	0.0262***	0.0260***
	(0.0010)	(0.0010)	(0.0011)	(0.0011)
# counties covered$_{b,t-1}$	0.000138***	0.000162***	0.000156***	0.000156***
	(0.0000040)	(0.0000040)	(0.0000044)	(0.0000044)
county FE	x	x		
quarter FE	x			
county x quarter FE			x	x
bank type x quarter FE		x	x	x
observations	240,635	240,635	207,877	207,877
R-squared	0.952	0.953	0.960	0.960
Within R2	0.0771	0.0249	0.0279	0.0275

Table 6: **The Asset Side of the SCB Balance Sheet**

Description: This table presents results on the consequences of deposit outflows on the asset side of the balance sheet for small community banks. For Panel A, the natural logarithm of commercial and industrial loans below 1 USD million on the balance sheet of small community b in county c and year t is the dependent variable in column 1, the natural logarithm of real estate loans on the balance sheet of small community bank b in county c and year t is column 2, the natural logarithm of individual loans on the balance sheet of small community bank b in county c and year t is column 3, the natural logarithm of other loans on the balance sheet of small community bank b in county c and year t is column 4. For Panel B, the natural logarithm of commercial and industrial loans below \$1 million on the balance sheet of small community b in county c and year t is the dependent variable. For Panel C, the percentage of nonaccrual commercial and industrial loans is the dependent variable in column 1, the percentage of still accruing past 30 days due commercial and industrial loans in column 2, the percentage of commercial and industrial loans charge-offs in column 3. Across panels, *sp. expansions* $_{c,t-1}$ captures MNOs spectrum expansions in county c and year $t-1$. In Panel B, *app available* $_{b,t-1}$ is a dummy equal to 1 if bank b offers a banking app in year $t-1$. Standard errors are clustered at the counties covered-year level; ***, **, *, $^{+}$ denote 1%, 5%, 10% and 15% statistical significance; - denotes a coefficient absorbed by fixed effects.

Panel A: Lending

	ln(C&I loans < 1 mill. $_{b,c,t}$)	ln(real estate loans $_{b,c,t}$)	ln(individual loans $_{b,c,t}$)	ln(other loans $_{b,c,t}$)
	(1)	(2)	(3)	(4)
sp. expansions$_{c,t-1}$	-0.0754**	0.0127	-0.000914	-0.000353
	(0.035)	(0.0091)	(0.021)	(0.026)
ln(population$_{c,t-1}$)	-2.832***	0.571***	0.0778	0.448
	(0.46)	(0.097)	(0.12)	(0.39)
# branches$_{b,c,t-1}$	0.0614***	0.0739***	0.0721***	0.127***
	(0.0056)	(0.0064)	(0.0077)	(0.013)
ln(GDP$_{c,t-1}$)	0.152*	0.00471	0.128***	0.0490
	(0.086)	(0.014)	(0.025)	(0.046)
ln(personal income pc$_{c,t-1}$)	-0.0289	0.0887	0.123*	-0.0630
	(0.17)	(0.063)	(0.064)	(0.095)
ln(small businesses$_{c,t-1}$)	0.641**	0.504***	-0.0548	-0.0614
	(0.26)	(0.065)	(0.073)	(0.21)
employment rate$_{c,t-1}$	-0.970**	-0.171**	0.142	0.813***
	(0.42)	(0.076)	(0.14)	(0.22)
NPLs over assets$_{b,t-1}$	4.813***	3.405***	2.177***	3.455***
	(1.30)	(0.37)	(0.30)	(0.58)
net income over assets$_{b,t-1}$	0.814	5.571***	7.213***	7.995***
	(1.51)	(0.87)	(0.90)	(1.66)
legacy in county$_{b,c,t-1}$	0.0310	-0.0167	-0.0618**	-0.105*
	(0.039)	(0.014)	(0.027)	(0.057)
# counties covered$_{b,t-1}$	0.0114	0.0486***	0.00700	0.0101
	(0.017)	(0.0058)	(0.0086)	(0.016)
county FE	x	x	x	x
year FE	x	x	x	x
bank FE	x	x	x	x
observations	48,282	48,282	48,282	48,282
R-squared	0.782	0.970	0.912	0.906
Within R2	0.00710	0.129	0.0168	0.0124

Panel B: Small Business Lending, Digitalization Channel

	ln(C&I loans < 1 mill.$_{b,t}$)			
	(1)	(2)	(3)	(4)
sp. expansions$_{c,t-1}$	-0.0754**		-0.251***	-
	(0.035)		(0.080)	
placebo sp. expansions$_{c,t-1}$		0.00718		
		(0.0081)		
app available$_{b,t-1}$			0.350***	0.508***
			(0.072)	(0.11)
app available$_{b,t-1}$ × sp. expansions$_{c,t-1}$			0.0939**	0.119*
			(0.040)	(0.061)
ln(population$_{c,t-1}$)	-2.832***	-2.833***	-3.133***	-
	(0.46)	(0.61)	(0.64)	
# branches$_{b,c,t-1}$	0.0614***	0.0612***	0.182***	0.186***
	(0.0056)	(0.0080)	(0.023)	(0.021)
ln(GDP$_{c,t-1}$)	0.152*	0.154	0.163	-
	(0.086)	(0.14)	(0.15)	
ln(personal income pc$_{c,t-1}$)	-0.0289	-0.0421	-0.269	-
	(0.17)	(0.28)	(0.30)	
ln(small businesses$_{c,t-1}$)	0.641**	0.645	0.338	-
	(0.26)	(0.49)	(0.51)	
employment rate$_{c,t-1}$	-0.970**	-1.024	-0.941	-
	(0.42)	(0.78)	(0.78)	
NPLs over assets$_{b,t-1}$	4.813***	4.869***	9.743***	8.909***
	(1.30)	(1.13)	(1.24)	(1.61)
net income over assets$_{b,t-1}$	0.814	0.807	23.89***	28.67***
	(1.51)	(1.82)	(4.62)	(5.83)
legacy in county$_{b,c,t-1}$	0.0310	0.0323	-0.847***	-0.870***
	(0.039)	(0.080)	(0.11)	(0.11)
# counties covered$_{b,t-1}$	0.0114	0.0123	-0.0945**	-0.110***
	(0.017)	(0.016)	(0.038)	(0.039)
county FE	x	x	x	
year FE	x	x	x	
county x year FE				x
bank FE	x	x		
observations	48,282	48,284	48,608	39,864
R-squared	0.782	0.782	0.396	0.446

Panel C: Small Business Loans Risk

	nonaccrual C&I loans $\%_{b,c,t}$	C&I loans accr. past due $\%_{b,c,t}$	C&I loans charge-offs $\%_{b,c,t}$
	(1)	(2)	(3)
sp. expansions$_{c,t-1}$	-0.430***	-0.338***	-0.0559
	(0.16)	(0.12)	(0.086)
ln(population$_{c,t-1}$)	0.748	-0.352	-0.794
	(1.32)	(1.10)	(0.63)
# branches$_{b,c,t-1}$	0.0122	0.0850***	0.0173
	(0.033)	(0.020)	(0.017)
ln(GDP$_{c,t-1}$)	-0.669**	0.333	0.00681
	(0.32)	(0.29)	(0.14)
ln(personal income pc$_{c,t-1}$)	-1.027^{+}	-0.762	-0.253
	(0.64)	(0.54)	(0.25)
ln(small businesses$_{c,t-1}$)	1.544*	0.424	0.167
	(0.83)	(0.85)	(0.51)
employment rate$_{c,t-1}$	-3.935***	-2.243*	0.569
	(1.52)	(1.30)	(0.61)
NPLs over assets$_{b,t-1}$	56.34***	13.42***	10.52***
	(5.96)	(3.56)	(2.21)
net income over assets$_{b,t-1}$	-27.58***	1.388	-4.745
	(8.72)	(5.79)	(5.03)
legacy in county$_{b,c,t-1}$	-0.0811	-0.149	0.103
	(0.17)	(0.21)	(0.075)
# counties covered$_{b,t-1}$	0.155**	0.0975^{+}	0.0289
	(0.063)	(0.060)	(0.030)
county FE	x	x	x
year FE	x	x	x
bank FE	x	x	x
observations	46,978	46,978	46,981
R-squared	0.403	0.264	0.212

Table 7: **Small Community Bank Branches Evolution**

Description: This table presents results on the effect of the mobile technology shock on bank branch closures for small community banks. The dependent variables are *at least one net closing* $_{c,t}$ in columns 1 and 2 and *at least one net opening* $_{c,t}$ in columns 3 and 4. *at least one net closing* $_{c,t}$ is a dummy variable equal to 1 if there has been at least one small community bank branch net closure in county c and year t, i.e. if the number of small community bank branches in county c and year t is smaller than the number of small community bank branches in year $t-1$. *at least one net opening* $_{c,t}$ is a dummy variable equal to 1 if there has been at least one small community bank branch net opening in county c and year t, i.e. if the number of small community bank branches in county c and year t is larger than the number of small community bank branches in year $t-1$. *sp. expansion* $_{c,t-1}$ (columns 1 and 3) captures MNOs spectrum expansion in county c and year $t-1$. *sp. exp. above* $Y-median$ $_{c,t-1}$ (columns 2 and 4) is a dummy variable equal to 1 if *sp. expansion* $_{c,t-1}$ is above the yearly median for the entire country for county c in year $t-1$. Standard errors are clustered at county level; ***, **, * denote 1%, 5%, and 10% statistical significance.

	at least one net closing $_{c,t}$		at least one net opening $_{c,t}$	
	(1)	(2)	(3)	(4)
sp. expansion $_{c,t-1}$	0.0583***		-0.0476***	
	(0.011)		(0.0097)	
sp. exp. above Y-median $_{c,t-1}$		0.0215***		-0.0235***
		(0.0052)		(0.0045)
# branches $_{c,t-1}$	0.0172***	0.0172***	-0.00421***	-0.00420***
	(0.0025)	(0.0025)	(0.00086)	(0.00086)
ln(population $_{c,t-1}$)	0.322***	0.314***	0.151**	0.161**
	(0.083)	(0.083)	(0.066)	(0.066)
ln(# businesses $_{c,t-1}$)	-0.0842**	-0.0899**	0.0734**	0.0771**
	(0.042)	(0.042)	(0.036)	(0.036)
employment rate $_{c,t-1}$	-0.129*	-0.103	0.0000476	-0.0193
	(0.070)	(0.070)	(0.061)	(0.061)
ln(personal income pc $_{c,t-1}$)	0.0361	0.0338	-0.0158	-0.0149
	(0.037)	(0.037)	(0.030)	(0.030)
ln(county GDP $_{c,t-1}$)	-0.0224	-0.0210	-0.0141	-0.0147
	(0.017)	(0.017)	(0.013)	(0.013)
county FE	x	x	x	x
year FE	x	x	x	x
observations	27,418	27,402	27,418	27,402
R-squared	0.247	0.247	0.203	0.203

Table 8: **Small Business Lending by Small Community Banks**

Description: This table presents results on the effect of the mobile technology shock on small business lending by small community banks. The dependent variables are the natural logarithm of the total number of commercial and industrial loans on the balance sheet of small community banks in county c and year t (based on their main county of operation according to deposits) in columns 1 and 2, the natural logarithm of the total amount of commercial and industrial loans on the balance sheet of small community banks in county c and year t (based on their main county of operation according to deposits) in columns 3 and 4. $sp.\ expansion_{\ c,t-1}$ (Columns 1 and 3) captures MNOs spectrum expansion in county c and year $t-1$. $sp.\ exp.\ above\ Y-median_{\ c,t-1}$ (Columns 2 and 4) is a dummy variable equal to 1 if $sp.\ expansion_{\ c,t-1}$ is above the yearly median for the entire country for county c in year $t-1$. Standard errors are clustered at county level; ***, **, * denote 1%, 5%, and 10% statistical significance.

	ln(# C&I loans < 1 mill. $_{b,c,t}$)		ln(am. C&I loans < 1 mill. $_{b,c,t}$)	
	(1)	(2)	(3)	(4)
sp. expansion $_{c,t-1}$	-0.110***		-0.152***	
	(0.038)		(0.055)	
sp. exp. above Y-median $_{c,t-1}$		-0.0288**		-0.0316*
		(0.013)		(0.018)
# branches $_{c,t-1}$	0.0336***	0.0336***	0.0363***	0.0363***
	(0.0064)	(0.0064)	(0.0071)	(0.0071)
ln(population $_{c,t-1}$)	-2.127***	-2.112***	-2.896***	-2.880***
	(0.33)	(0.33)	(0.44)	(0.44)
ln(county GDP $_{c,t-1}$)	0.0330	0.0345	0.0601	0.0627
	(0.064)	(0.064)	(0.089)	(0.090)
ln(personal income pc $_{c,t-1}$)	0.385**	0.379**	0.497**	0.488**
	(0.16)	(0.16)	(0.24)	(0.24)
ln(# small businesses $_{c,t-1}$)	0.287	0.296	0.371	0.382
	(0.20)	(0.20)	(0.30)	(0.30)
employment rate $_{c,t-1}$	-0.243	-0.308	-0.303	-0.397
	(0.33)	(0.33)	(0.42)	(0.41)
county FE	x	x	x	x
year FE	x	x	x	x
observations	20,272	20,272	20,272	20,272
R-squared	0.843	0.843	0.813	0.813

Table 9: **Small Business Lending by Other Banks**

Description: This table presents results on the effect of the mobile technology shock on small business lending by the big community banks, the large banks, and the big 4 banks filing CRA reports. The dependent variables are the natural logarithm of the amount of CRA loans originated locally in county c and year t by bank b in Panel A, and the natural logarithm of the amount of CRA loans originated remotely in county c and year t by bank b. Across panels, *sp. expansion* $_{c,t-1}$ captures MNOs spectrum expansion in county c and year $t-1$. In Panel B, *app available* $_{b,t-1}$ is a dummy equal to 1 if bank b offers a banking app in year $t-1$. Standard errors are clustered at county level; ***, **, * denote 1%, 5%, and 10% statistical significance.

Panel A: small business loans to borrowers in counties where lender operates branches

	ln(am. local SBLs$_{c,t}$)			
	(1)	(2)	(3)	(4)
sp. expansions$_{t-1}$	0.00325	-0.0242	-0.0320	-0.0385
	(0.027)	(0.026)	(0.021)	(0.026)
ln(population$_{c,t-1}$)	1.234***	1.079***	0.767***	0.560**
	(0.25)	(0.25)	(0.21)	(0.23)
# branches$_{c,t-1}$	0.0410***	0.0391***	0.0349***	0.0352***
	(0.0073)	(0.0072)	(0.0064)	(0.0067)
employment rate$_{c,t-1}$	-0.638*	-0.570*	0.0190	0.244
	(0.34)	(0.34)	(0.28)	(0.29)
ln(# small businesses$_{c,t-1}$)	0.778***	0.693***	0.522***	0.439***
	(0.18)	(0.18)	(0.14)	(0.15)
ln(county GDP$_{c,t-1}$)	0.0396	0.0671	0.0682	0.0917**
	(0.057)	(0.055)	(0.044)	(0.045)
NPLs over assets$_{b,t-1}$	-5.839***	-6.951***	0.252	-
	(0.96)	(0.93)	(0.69)	
net income over assets$_{b,t-1}$	-4.479***	-4.245**	-2.778***	-
	(1.73)	(1.70)	(0.75)	
legacy in county$_{b,c,t-1}$	0.856***	0.857***	0.600***	0.594***
	(0.043)	(0.042)	(0.036)	(0.038)
# counties covered$_{b,t-1}$	-0.000589***	-0.00135***	-0.00153***	-
	(0.000059)	(0.00011)	(0.000067)	
county FE	x	x	x	x
year FE	x	x	x	x
bank FE			x	
bank type x year FE		x	x	x
bank x year FE				x
observations	107,158	107,158	107,136	106,423
R-squared	0.444	0.467	0.731	0.750
Within R2	0.138	0.141	0.142	0.146

Panel B: small business loans to borrowers in counties where lender does not operate branches

	ln(am. local SBLs$_{c,t}$)					
	(1)	(2)	(3)	(4)	(5)	(6)
sp. expansions$_{t-1}$	0.0275**	0.0265**	0.0438***	0.0511***	0.00873	-
	(0.013)	(0.013)	(0.012)	(0.014)	(0.014)	
app available$_{b,t-1}$					-0.172***	-0.189***
					(0.010)	(0.010)
app available$_{b,t-1}$ × sp. expansions$_{t-1}$					0.0526***	0.0608***
					(0.0069)	(0.0070)
ln(population$_{c,t-1}$)	0.959***	0.920***	0.755***	1.204***	0.786***	-
	(0.12)	(0.12)	(0.11)	(0.13)	(0.11)	
employment rate$_{c,t-1}$	0.326**	0.263**	0.193	0.420***	0.201	-
	(0.13)	(0.13)	(0.12)	(0.13)	(0.12)	
ln(# small businesses$_{c,t-1}$)	0.194***	0.244***	0.306***	0.326***	0.309***	-
	(0.069)	(0.069)	(0.066)	(0.069)	(0.066)	
ln(county GDP$_{c,t-1}$)	-0.0140	0.0214	0.0433*	0.0349	0.0440**	-
	(0.023)	(0.023)	(0.022)	(0.022)	(0.022)	
NPLs over assets$_{b,t-1}$	2.633***	12.17***	5.839***	0	5.881***	6.149***
	(0.52)	(0.52)	(0.45)		(0.45)	(0.46)
net income over assets$_{b,t-1}$	5.732***	7.376***	3.306***	0	3.384***	3.267***
	(0.41)	(0.43)	(0.40)		(0.41)	(0.41)
# counties covered$_{b,t-1}$	0.00118***	0.000394***	0.000383***	0	0.000451***	0.000444***
	(0.000018)	(0.000022)	(0.000051)		(0.000051)	(0.000052)
county FE	x	x	x	x	x	
year FE	x	x	x	x	x	
county x year FE						x
bank FE			x		x	x
bank type x year FE		x	x	x	x	x
bank x year FE				x		
observations	641,502	641,502	641,496	641,344	641,496	641,474
R-squared	0.262	0.284	0.469	0.499	0.470	0.485

Table 10: **The Role of Fintech**

Description: This table presents results on the effect of the mobile technology shock on small business lending by banks *versus* FinTech. The dependent variables are the first difference in the number of secured small business loans granted by banks in county c and year t in columns 1 and 2, the first difference in the number of secured small business loans granted by FinTech in county c and year t in columns 3 and 4. Data are from UCC Filings courtesy of Gopal and Schnabl (2020). $sp.\ expansion_{\,c,t-1}$ (columns 1 and 3) captures MNOs spectrum expansion in county c and year $t-1$. $sp.\ exp.\ above\ Y-median_{\,c,t-1}$ (columns 2 and 4) is a dummy variable equal to 1 if $sp.\ expansion_{\,c,t-1}$ is above the yearly median for the entire country for county c in year $t-1$. Standard errors are clustered at county level; ***, **, * denote 1%, 5%, and 10% statistical significance.

	Δ bank SBLs $_{c,t,t-1}$		Δ FinTech SBLs $_{c,t,t-1}$	
	(1)	(2)	(3)	(4)
sp. expansion $_{c,t-1}$	-5.313***		2.759***	
	(1.80)		(0.67)	
sp. exp. above Y-median $_{c,t-1}$		-2.730***		0.791***
		(1.01)		(0.23)
# branches $_{c,t-1}$	-2.745***	-2.745***	1.189***	1.194***
	(1.01)	(1.01)	(0.42)	(0.42)
ln(population $_{c,t-1}$)	-113.2***	-112.9***	88.29***	88.34***
	(26.3)	(26.3)	(13.1)	(13.1)
ln(# small businesses $_{c,t-1}$)	-8.626*	-8.647*	3.894*	3.826*
	(4.90)	(4.87)	(2.20)	(2.21)
employment rate $_{c,t-1}$	16.28*	15.39	12.71***	13.48***
	(9.57)	(9.49)	(3.54)	(3.58)
ln(personal income pc $_{c,t-1}$)	-23.02***	-22.75***	-0.0526	-0.316
	(6.00)	(6.00)	(1.70)	(1.70)
ln(county GDP $_{c,t-1}$)	0.455	0.410	-3.566***	-3.553***
	(1.84)	(1.84)	(0.67)	(0.67)
county FE	x	x	x	x
year FE	x	x	x	x
observations	21,090	21,077	21,090	21,077
R-squared	0.231	0.231	0.641	0.641

Table 11: **Real Effects**

Description: This table presents results on the real effects of the mobile technology shock on small businesses via the small community bank channel. The dependent variables are small businesses' employment growth in county c and year t in Panel A, small businesses' wage growth in county c and year t in Panel B, small businesses' growth rate in county c and year t in Panel C. $SCB\ deposits\%_{c,2010}$ is small community banks' deposits over total deposits in county c in 2010, *sp. expansion* $_{c,t-1}$, captures MNOs spectrum expansion in county c and year $t-1$. Standard errors are clustered at county level; ***, **, *, $^{+}$ denote 1%, 5%,, 10% and 15% statistical significance; - denotes a coefficient absorbed by fixed effects.

Panel A: Employment Growth

	employment growth$_{c,t}$		
	(1) firm size: 1-19 employees	(2) firm size: 20-49 employees	(3) firm size: 50-499 employees
sp. exp.$_{c,t-1}$	0.00239	-0.00881*	0.0205
	(0.0018)	(0.0051)	(0.013)
SCB deposits %$_{c,2010}$	-	-	-
sp. exp.$_{c,t-1}$ × SCB deposits %$_{c,2010}$	-0.00593***	-0.00782^{+}	-0.0129
	(0.0017)	(0.0048)	(0.0096)
# branches$_{t-1}$	-0.0000668	-0.000113	-0.000248**
	(0.000052)	(0.00011)	(0.00012)
ln(population$_{t-1}$)	-0.0727**	-0.0381	0.00635
	(0.030)	(0.055)	(0.082)
employment rate$_{c,t}$	-0.00803	0.0892	0.0293
	(0.026)	(0.069)	(0.10)
ln(personal income pc$_{c,t-1}$)	0.0270**	0.0521*	0.0774^{+}
	(0.011)	(0.031)	(0.049)
ln(county GDP$_{c,t-1}$)	-0.00366	0.00654	0.00950
	(0.0047)	(0.013)	(0.019)
county FE	x	x	x
year FE	x	x	x
observations	27,708	27,149	26,209
R-squared	0.146	0.0951	0.120

Panel B: Wage Growth

	wage growth$_{c,t}$		
	(1) firm size: 1-19 employees	(2) firm size: 20-49 employees	(3) firm size: 50-499 employees
sp. exp.$_{c,t-1}$	0.00567***	0.00676**	0.0124***
	(0.0016)	(0.0034)	(0.0043)
SCB deposits %$_{c,2010}$	-	-	-
sp. exp.$_{c,t-1}$ × SCB deposits %$_{c,2010}$	-0.00522***	-0.00601**	0.000207
	(0.0013)	(0.0027)	(0.0039)
# branches$_{t-1}$	-0.000197***	-0.000206***	-0.0000199
	(0.000057)	(0.000073)	(0.000080)
ln(population$_{t-1}$)	-0.0137	-0.0112	-0.0311
	(0.017)	(0.025)	(0.028)
employment rate$_{c,t}$	-0.0437^{+}	-0.123***	-0.0255
	(0.029)	(0.048)	(0.056)
ln(personal income pc$_{c,t-1}$)	0.0220**	0.0244	0.00403
	(0.0098)	(0.017)	(0.022)
ln(county GDP$_{c,t-1}$)	0.00325	-0.00389	0.00409
	(0.0043)	(0.0080)	(0.010)
county FE	x	x	x
year FE	x	x	x
observations	27,708	27,514	26,275
R-squared	0.0889	0.0733	0.0739

Panel C: Economic Growth

	# of small businesses' growth$_{c,t}$			county GDP growth$_t$
	(1) firm size: 1-19 employees	(2) firm size: 20-49 employees	(3) firm size: 50-499 employees	(4)
sp. exp.$_{c,t-1}$	0.00232*	0.00734*	0.00136	0.0391***
	(0.0013)	(0.0043)	(0.0048)	(0.0046)
SCB deposits %$_{c,2010}$	-	-	-	-
sp. exp.$_{c,t-1}$ × SCB deposits %$_{c,2010}$	-0.00358***	-0.0122***	0.00461	-0.0356***
	(0.0011)	(0.0037)	(0.0051)	(0.0040)
# branches$_{t-1}$	-0.0000232	-0.000250**	-0.000319***	-0.000689***
	(0.000042)	(0.00011)	(0.00012)	(0.00016)
ln(population$_{t-1}$)	0.00851	-0.0656*	-0.111*	-0.000846
	(0.021)	(0.035)	(0.063)	(0.054)
employment rate$_{c,t}$	0.0151	-0.0484	-0.211***	-0.0460
	(0.019)	(0.067)	(0.074)	(0.087)
ln(personal income pc$_{c,t-1}$)	0.0200***	0.0514*	0.0147	-0.517***
	(0.0072)	(0.028)	(0.035)	(0.026)
ln(county GDP$_{c,t-1}$)	-0.00245	-0.0133	-0.00889	
	(0.0034)	(0.013)	(0.015)	
county FE	x	x	x	x
year FE	x	x	x	x
observations	28,081	25,615	21,921	28,084
R-squared	0.142	0.113	0.150	0.221

Appendices to:

Keeping up in digital era:
a traditional bank perspective.

(intended for online publication)

A Variable Descriptions

Name	Explanation
ln(deposits$_{c,t}$)	Natural logarithm of deposits in county c and year t. *Source: FDIC Summary of Deposits.*
ln(deposits$_{b,c,t}$)	Natural logarithm of bank b deposits in county c and year t. *Source: FDIC Summary of Deposits.*
sp. expansions$_{c,t}$	Additional spectrum allotted to Mobile Network Operators in county c and year t since 2010 (hundreds of MHz). *Source: based on Federal Communication Commission Licenses.*
app available$_{b,t}$	Takes value of 1 if bank b provides mobile banking services in year t. *Source: hand-collected from data.ai.*
# branches$_{c,t}$	Number of branches of bank b in county c and year t. *Source: FDIC Summary of Deposits.*
ln(population$_{c,t}$)	Natural logarithm of county c population in year t. *Source: Census Bureau.*
ln(# businesses$_{c,t}$)	Natural logarithm of county c # of businesses in year t. *Source: Census County Business Patterns.*
employment rate$_{c,t}$	employment rate [0,1] of county c in year t. *Source: Bureau of Labor Statistics.*
ln(personal income pc$_{c,t}$)	Natural logarithm of personal income per capita in county c and year t. *Source: Bureau of Economic Analysis.*
ln(county GDP$_{c,t}$)	Natural logarithm of county c GDP in year t. *Source: Bureau of Economic Analysis.*
NPLs over assets$_{b,t}$	ratio of nonperforming loans over assets of bank b in year t. *Source: Call Reports.*
net income over assets$_{b,t}$	ratio of net income over assets of bank b in year t. *Source: Call Reports.*
# counties covered$_{b,t}$	number of counties where bank b has branches in year t. *Source: FDIC Summary of Deposits.*
legacy in county$_{b,c,t}$	dummy equal to one if bank b runs a branch in county c and year t that has been serving the county for more than 43 years (median sample branch age). *Source: FDIC Summary of Deposits.*
big community bank$_{b,t}$	Takes the value of 1 if bank b is a *big community bank* in year t. *Source: bank type framework (Section 4).*
large bank$_{b,t}$	Takes the value of 1 if bank b is a *large bank* in year t. *Source: bank type framework (Section 4).*
big4 bank$_{b,t}$	Takes the value of 1 if bank b is a *big4 bank* in year t. *Source: bank type framework (Section 4).*
non-community bank$_{b,t}$	Takes the value of 1 if bank b is either a *large bank* or a *big4 bank* in year t. *Source: bank type framework (Section 4).*

Name	Description
non-community bank$_{b,t}$	Takes the value of 1 if bank b is either a *large bank* or a *big4 bank* in year t. *Source: bank type framework (Section 4).*
deposit-weighted avg sp. expansions$_{b,t}$	deposit-weighted average of *sp. expansions*$_{c,t}$ across the counties bank b operates in. *Source: based on FCC Licenses & FDIC Summary of Deposits.*
deposit-weighted % pop. 65y and older$_{b,t}$	deposit-weighted average of the percentage [0,1] of population 65-year and older across the counties bank b operates in in year t. *Source: based on Census 2010 & FDIC Summary of Deposits.*
dep.-w. avg % of pop. w/higher ed.$_{b,t}$	deposit-weighted average of the percentage [0,1] of population with higher education across the counties bank b operates in in year t. *Source: based on Census 2010 & FDIC Summary of Deposits.*
% branches providing app$_{c,t}$	percentage [0,1] of county c branches belonging to banks that provide mobile banking services in year t. *Source: based on DIC Summary of Deposits & hand-collected from data.ai.*
% deposits with app$_{c,t}$	percentage [0,1] of county c deposits belonging to banks that provide mobile banking services in year t. *Source: based on DIC Summary of Deposits & hand-collected from data.ai.*
% population 65y and older$_{c,2010}$	percentage [0,1] of population 65-year and older in county c in 2010. *Source: Census 2010.*
% population w/higher education$_{c,2010}$	percentage [0,1] of population with higher education in county c in 2010. *Source: Census 2010.*
I(big comm. bank branches$_{c,t}$)	Takes the value of 1 if there is at least one branch belonging to a *big community bank* in county c and year t. *Source: FDIC Summary of Deposits & bank type framework (Section 4).*
I(non-comm. bank branches$_{c,t}$)	Takes the value of 1 if there is at least one branch belonging to a *non-community bank* in county c and year t. *Source: FDIC Summary of Deposits & bank type framework (Section 4).*
interest paid %$_{b,c,t}$	(total interest expenses / total deposits)*100 for bank b in year t - bank b having a branch in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits.*
net interest paid %$_{b,c,t}$	((total interest expenses - total fees) / total deposits)*100 for bank b in year t - bank b having a branch in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits.*
ln(C&I loans < 1 mill.$_{b,c,t}$)	Natural logarithm of the total amount of commercial and industrial loans below 1 million on the balance sheet of bank b in year t - bank b conducting the majority of its business in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits.*
ln(real estate loans$_{b,c,t}$)	Natural logarithm of the total amount of real estate loans on the balance sheet of bank b in year t - bank b conducting the majority of its business in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits.*
ln(individual loans$_{b,c,t}$)	Natural logarithm of the total amount of individual loans (car loans, student loans, etc.) on the balance sheet of bank b in year t - bank b conducting the majority of its business in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits.*
ln(other loans$_{b,c,t}$)	Natural logarithm of the total amount of individual loans (loans to other institutions, farm loans, etc.) on the balance sheet of bank b in year t - bank b conducting the majority of its business in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits.*
ln(# small businesses$_{c,t}$)	Natural logarithm of county c # of businesses with less than 50 employees in year t. *Source: Census County Business Patterns.*

Name	Description
nonaccrual C&I loans $\%_{b,c,t}$	(nonaccrual C&I loans / total C&I loans)*100 for bank b in year t - bank b conducting the majority of its business in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits.*
C&I loans accr. past due $\%_{b,c,t}$	(C&I loans still accruing but past due/ total C&I loans)*100 for bank b in year t - bank b conducting the majority of its business in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits.*
C&I loans charge-offs $\%_{b,c,t}$	(C&I loans charge-offs/ total C&I loans)*100 for bank b in year t - bank b conducting the majority of its business in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits.*
at least one net closing$_{c,t}$	Takes the value of 1 if the number of small community bank branches in county c and year t is smaller than the number of small community bank branches in county c and year $t-1$. *Source: FDIC Summary of Deposits.*
at least one net opening$_{c,t}$	Takes the value of 1 if the number of small community bank branches in county c and year t is greater than the number of small community bank branches in county c and year $t-1$. *Source: FDIC Summary of Deposits.*
ln(# branches$_{c,t}$)	Natural logarithm of the total number of bank branches in county c and year t. *Source: FDIC Summary of Deposits.*
ln(# C&I loans < 1 mill.$_{b,c,t}$)	Natural logarithm of the number of commercial and industrial loans below 1 million on the balance sheet of bank b in year t - bank b conducting the majority of its business in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits.*
ln(am. C&I loans < 1 mill.$_{b,c,t}$)	Natural logarithm of the amount of commercial and industrial loans below 1 million on the balance sheet of bank b in year t - bank b conducting the majority of its business in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits.*
ln(amount CRA SBLs$_{c,t}$)	total amount of small business loans originated in county c and year t by (either big community or non-community) banks that file report under the CRA and that have a branch in the county. *Source: CRA & FDIC Summary of Deposits.*
Δ bank SBLs$_{c,t,t-1}$	number of secured, non-real estate small business loans originated by banks in county c and year t minus number of secured, non-real estate small business loans originated by banks in county c and year $t-1$. *Source: Gopal and Schnabl (2020).*
Δ FinTech SBLs$_{c,t,t-1}$	number of secured, non-real estate small business loans originated by FinTech firms in county c and year t minus number of secured, non-real estate small business loans originated by FinTech firms in county c and year $t-1$. *Source: Gopal and Schnabl (2020).*
employment growth$_{c,t}$	year-on-year growth in the number of employees working at the respective firm type in county c and year t. *Source: Quarterly Workforce Indicators.*
wage growth$_{c,t}$	year-on-year growth in the wage of employees working at the respective firm type in county c and year t. *Source: Quarterly Workforce Indicators.*
# of small businesses' growth$_{c,t}$	year-on-year growth in the number of businesses in county c and year t. *Source: Quarterly Workforce Indicators.*
county GDP growth$_{c,t}$	year-on-year GDP growth for county c and year t. *Source: Bureau of Economic Analysis.*

B Geographical distribution of effects

This Appendix replicates the main results in the paper within three geographical subsamples:

- counties belonging to a *metropolitan statistical area* (henceforth MeSA);
- counties belonging to a *micropolitan statistical area* (henceforth MiSA);
- remaining countries (henceforth rural).

According to the Census Bureau, "The United States Office of Management and Budget delineates metropolitan and micropolitan statistical areas. [...] Each metropolitan statistical area must have at least one urbanized area of 50,000 or more inhabitants. Each micropolitan statistical area must have at least one urban cluster of at least 10,000 but less than 50,000 population". I rely on conversion tables between counties and statistical areas provided by the U.S. Bureau of Labor Statistics in cooperation with the Census Bureau.

Table B.1: **Technology-driven Competition on Deposits**

Description: This table presents results on deposit competition introduced by the different mobile technology adoption rates across the 3 bank types (*small community banks*, *big community banks*, *non-community banks*). Panel A covers deposit movements, Panel B interest rates on deposits. Column 1 has estimations on the full sample, Column 2 on the counties belonging to a metropolitan statistical area (MeSA), Column 3 on the counties belonging to a micropolitan statistical area (MiSA), Column 4 on the remaining counties (rural). Standard errors are clustered at county level; ***, **, * denote 1%, 5%, and 10% statistical significance.

Panel A: Deposit Flows

	ln(county deposits$_{b,c,t}$)			
	(1) full sample	(2) MeSA	(3) MiSA	(4) rural
sp. expansions $_{c,t-1}$	-0.0273**	-0.0475**	-0.0144	-0.0300**
	(0.014)	(0.020)	(0.022)	(0.015)
big community bank $_{b,t}$	0.382***	0.525***	0.125***	0.122***
	(0.038)	(0.051)	(0.044)	(0.042)
non-community bank $_{b,t}$	0.143***	0.372***	-0.135***	-0.190***
	(0.049)	(0.067)	(0.037)	(0.032)
big community bank $_{b,t}$ × sp. expansions $_{c,t-1}$	0.0254*	0.0410**	0.0476*	0.0185
	(0.014)	(0.018)	(0.025)	(0.018)
non-community bank $_{b,t}$ × sp. expansions $_{c,t-1}$	0.123***	0.149***	0.109***	0.0982***
	(0.011)	(0.014)	(0.015)	(0.013)
ln(population $_{c,t-1}$)	0.520***	0.0787	0.804***	0.724***
	(0.11)	(0.18)	(0.20)	(0.14)
# county branches $_{b,c,t-1}$	0.0905***	0.0825***	0.477***	0.486***
	(0.015)	(0.013)	(0.013)	(0.016)
ln(# businesses $_{c,t-1}$)	0.158**	0.268**	0.0917	-0.0162
	(0.066)	(0.13)	(0.14)	(0.076)
employment rate $_{c,t-1}$	0.358**	0.491	0.445	0.102
	(0.15)	(0.36)	(0.31)	(0.14)
ln(personal income pc $_{c,t-1}$)	0.201***	0.164*	0.408***	0.141***
	(0.044)	(0.087)	(0.098)	(0.048)
ln(county GDP $_{c,t-1}$)	0.0858***	0.140***	0.0415	0.0581**
	(0.022)	(0.048)	(0.047)	(0.024)
county FE	x	x	x	x
year FE	x	x	x	x
observations	222,212	132,886	41,185	48,141
R-squared	0.418	0.422	0.449	0.446

Panel B: Interest Rate on Deposits

	interest paid % $_{b,c,t}$			
	(1) full sample	(2) MeSA	(3) MiSA	(4) rural
sp. expansions $_{c,t-1}$	-0.0378***	-0.0329***	-0.0535***	-0.0493***
	(0.0027)	(0.0037)	(0.0060)	(0.0049)
big community bank $_{b,t}$	-0.0552***	-0.0627***	-0.0503***	-0.0240***
	(0.0028)	(0.0038)	(0.0060)	(0.0055)
non-community bank $_{b,t}$	-0.192***	-0.187***	-0.212***	-0.190***
	(0.0019)	(0.0026)	(0.0038)	(0.0037)
big community bank $_{b,t}$ × sp. expansions $_{c,t-1}$	0.0239***	0.0277***	0.0194***	0.00937***
	(0.0018)	(0.0024)	(0.0040)	(0.0035)
non-community bank $_{b,t}$ × sp. expansions $_{c,t-1}$	0.0767***	0.0743***	0.0882***	0.0733***
	(0.0012)	(0.0017)	(0.0026)	(0.0024)
# county branches $_{b,c,t-1}$	-0.00155***	-0.00154***	-0.00549***	-0.00448***
	(0.000061)	(0.000068)	(0.00058)	(0.00079)
ln(population $_{c,t-1}$)	-0.0429*	-0.0817**	-0.0591	-0.00536
	(0.025)	(0.041)	(0.059)	(0.044)
ln(county GDP $_{c,t-1}$)	-0.0383***	-0.0417***	-0.0605***	-0.0195**
	(0.0064)	(0.012)	(0.013)	(0.0079)
ln(personal income pc $_{c,t-1}$)	-0.000849	0.0725***	-0.0267	-0.0689***
	(0.012)	(0.022)	(0.027)	(0.016)
ln(# businesses $_{c,t-1}$)	0.147***	0.173***	0.158***	0.102***
	(0.018)	(0.030)	(0.040)	(0.022)
employment rate $_{c,t-1}$	-0.153***	-0.211**	-0.180**	-0.122**
	(0.042)	(0.085)	(0.076)	(0.050)
county FE	x	x	x	x
year FE	x	x	x	x
observations	223,535	134,121	41,224	48,190
R-squared	0.475	0.429	0.530	0.591

Table B.2: **The Asset Side of the Balance Sheet**

Description: This table presents results on different types of lending - Column 1 commercial and industrial loans below 1 USD M, Column 2 real estate loans, Column 3 individual loans, Column 4 other loans. Panel A has estimations on the full sample, Panel B on the counties belonging to a metropolitan statistical area (MeSA), Panel C on the counties belonging to a micropolitan statistical area (MiSA), Panel D on the remaining counties (rural). Standard errors are clustered at county level; ***, **, * denote 1%, 5%, and 10% statistical significance.

Panel A: full sample

	(1)	(2)	(3)	(4)
	ln(C&I loans < 1 mill. $_{b,t}$)	ln(real estate loans $_{b,t}$)	ln(individual loans $_{b,t}$)	ln(other loans $_{b,t}$)
sp. expansions $_{c,t-1}$	-0.152***	-0.0108	-0.0362	-0.111*
	(0.055)	(0.030)	(0.042)	(0.064)
ln(population $_{c,t-1}$)	-2.896***	-1.386***	-1.535***	-2.235***
	(0.44)	(0.28)	(0.38)	(0.56)
# county branches $_{c,t-1}$	0.0363***	0.0309***	0.0335***	0.0489***
	(0.0071)	(0.0060)	(0.0067)	(0.0099)
ln(county GDP $_{c,t-1}$)	0.0601	0.0717	0.111*	0.0648
	(0.089)	(0.049)	(0.057)	(0.10)
ln(personal income pc $_{c,t-1}$)	0.497**	0.0255	0.190	-0.0719
	(0.24)	(0.11)	(0.14)	(0.24)
ln(# small businesses $_{c,t-1}$)	0.371	0.591***	0.210	0.0240
	(0.30)	(0.15)	(0.24)	(0.27)
employment rate $_{c,t-1}$	-0.303	-0.606**	-0.102	-0.150
	(0.42)	(0.26)	(0.29)	(0.47)
county FE	x	x	x	x
year FE	x	x	x	x
observations	20,272	20,272	20,272	20,272
R-squared	0.813	0.905	0.849	0.845

Panel B: metropolitan statistical areas

	(1)	(2)	(3)	(4)
	ln(C&I loans < 1 mill. $_{b,t}$)	ln(real estate loans $_{b,t}$)	ln(individual loans $_{b,t}$)	ln(other loans $_{b,t}$)
sp. expansions $_{c,t-1}$	-0.219**	0.0492	0.0236	-0.0361
	(0.10)	(0.049)	(0.083)	(0.13)
ln(population $_{c,t-1}$)	-2.688***	-1.673***	-1.099*	-0.760
	(0.77)	(0.49)	(0.67)	(1.20)
# county branches $_{c,t-1}$	0.0269***	0.0236***	0.0266***	0.0402***
	(0.0062)	(0.0054)	(0.0062)	(0.0097)
ln(county GDP $_{c,t-1}$)	0.0117	-0.0354	-0.0953	-0.157
	(0.21)	(0.13)	(0.16)	(0.34)
ln(personal income pc $_{c,t-1}$)	0.253	0.422	0.156	-0.0521
	(0.86)	(0.31)	(0.45)	(1.01)
ln(# small businesses $_{c,t-1}$)	0.493	0.669**	-0.0161	-0.865
	(0.52)	(0.32)	(0.43)	(0.83)
employment rate $_{c,t-1}$	-2.733**	-2.775***	-2.084**	-1.923
	(1.29)	(0.78)	(1.06)	(1.94)
county FE	x	x	x	x
year FE	x	x	x	x
observations	8,243	8,243	8,243	8,243
R-squared	0.834	0.880	0.829	0.811

Panel C: micropolitan statistical areas

	(1) ln(C&I loans < 1 mill. $_{b,t}$)	(2) ln(real estate loans $_{b,t}$)	(3) ln(individual loans $_{b,t}$)	(4) ln(other loans $_{b,t}$)
sp. expansions $_{c,t-1}$	-0.00463	-0.0282	-0.0573	-0.132
	(0.083)	(0.064)	(0.075)	(0.12)
ln(population $_{c,t-1}$)	-0.912	-0.322	-0.0467	-1.419
	(0.77)	(0.69)	(0.68)	(1.12)
# county branches $_{c,t-1}$	0.0964***	0.0810***	0.0825***	0.118***
	(0.013)	(0.0083)	(0.0086)	(0.015)
ln(county GDP $_{c,t-1}$)	0.112	0.0600	0.0975	0.0905
	(0.15)	(0.11)	(0.13)	(0.20)
ln(personal income pc $_{c,t-1}$)	0.898**	0.373	0.652**	0.214
	(0.40)	(0.28)	(0.30)	(0.40)
ln(# small businesses $_{c,t-1}$)	-0.302	0.0774	-0.538	0.331
	(0.52)	(0.31)	(0.35)	(0.63)
employment rate $_{c,t-1}$	1.032	0.596	1.448**	0.314
	(0.73)	(0.51)	(0.64)	(1.05)
county FE	x	x	x	x
year FE	x	x	x	x
observations	4,422	4,422	4,422	4,422
R-squared	0.837	0.876	0.874	0.886

Panel D: rural areas

	(1) ln(C&I loans < 1 mill. $_{b,t}$)	(2) ln(real estate loans $_{b,t}$)	(3) ln(individual loans $_{b,t}$)	(4) ln(other loans $_{b,t}$)	(5) ln(farm loans < 0.5 mill. $_{b,t}$)
sp. expansions $_{c,t-1}$	-0.0743	-0.0397	-0.00939	-0.108	-0.364***
	(0.063)	(0.039)	(0.047)	(0.076)	(0.13)
ln(population $_{c,t-1}$)	-0.561	0.628	0.950**	-0.723	-1.030
	(0.83)	(0.47)	(0.46)	(0.85)	(1.22)
# county branches $_{c,t-1}$	0.130***	0.112***	0.110***	0.139***	0.142***
	(0.015)	(0.0093)	(0.0098)	(0.016)	(0.020)
ln(county GDP $_{c,t-1}$)	-0.0510	0.0497	0.0799	0.0267	-0.463**
	(0.12)	(0.054)	(0.064)	(0.11)	(0.19)
ln(personal income pc $_{c,t-1}$)	0.554**	-0.0952	0.201	-0.0697	0.458
	(0.25)	(0.11)	(0.14)	(0.19)	(0.30)
ln(# small businesses $_{c,t-1}$)	0.579	0.697***	0.525*	0.295	0.338
	(0.42)	(0.18)	(0.29)	(0.23)	(0.48)
employment rate $_{c,t-1}$	-0.106	-0.454	-0.0691	0.245	-0.454
	(0.53)	(0.31)	(0.31)	(0.44)	(0.89)
county FE	x	x	x	x	x
year FE	x	x	x	x	x
observations	7,607	7,607	7,607	7,607	7,607
R-squared	0.751	0.913	0.887	0.876	0.877

Table B.3: **The Role of FinTech**

Description: This table presents results on the effect of the mobile technology shock on small business lending by FinTech. The dependent variable is the number of secured small business loans granted by FinTech in county c and year t minus the corresponding number the previous year. Column 1 has estimations on the full sample, Column 2 on the counties belonging to a metropolitan statistical area (MeSA), Column 3 on the counties belonging to a micropolitan statistical area (MiSA), Column 4 on the remaining counties (rural). FinTech data are from UCC Filings courtesy of Gopal and Schnabl (2020). Standard errors are clustered at county level; ***, **, * denote 1%, 5%, and 10% statistical significance.

	# FinTech SBLs $_{c,t}$ - # FinTech SBLs $_{c,t-1}$			
	(1)	(2)	(3)	(4)
	full sample	MeSA	MiSA	rural
sp. expansions $_{c,t-1}$	2.759***	4.643***	-0.257	0.147*
	(0.67)	(1.72)	(0.29)	(0.081)
ln(population $_{c,t-1}$)	88.29***	127.5***	7.423***	0.260
	(13.1)	(25.8)	(2.80)	(0.62)
# county branches $_{b,c,t-1}$	1.189***	1.159***	0.00656	0.00568
	(0.42)	(0.45)	(0.033)	(0.034)
ln(# small businesses $_{c,t-1}$)	3.894*	42.36***	-0.0573	-0.241
	(2.20)	(10.2)	(1.06)	(0.23)
employment rate $_{c,t-1}$	12.71***	85.73***	2.489	1.220***
	(3.54)	(18.2)	(1.89)	(0.40)
ln(personal income pc $_{c,t-1}$)	-0.0526	16.91*	-1.359	-0.254
	(1.70)	(10.1)	(0.99)	(0.19)
ln(county GDP $_{c,t-1}$)	-3.566***	-9.086***	-0.610	-0.0691
	(0.67)	(2.48)	(0.38)	(0.100)
county FE	x	x	x	x
year FE	x	x	x	x
observations	21,090	7,745	4,379	8,966
R-squared	0.641	0.649	0.137	0.0907

Table B.4: **Real Effects**

Description: This table presents results on the real effects of the mobile technology shock on small businesses via the small community bank channel. The dependent variable is county GDP growth. Column 1 has estimations on the full sample, Column 2 on the counties belonging to a metropolitan statistical area (MeSA), Column 3 on the counties belonging to a micropolitan statistical area (MiSA), Column 4 on the remaining counties (rural). Standard errors are clustered at county level; ***, **, *, $^{+}$ denote 1%, 5%,, 10% and 15% statistical significance.

	county GDP growth $_{c,t-1}$			
	(1) full sample	(2) MeSA	(3) MiSA	(4) rural
sp. exp. $_{c,t-1}$	0.0391***	0.0154***	0.0153	0.0541***
	(0.0046)	(0.0039)	(0.010)	(0.0090)
SCB deposits % $_{c,2010}$	-	-	-	-
sp. exp. $_{c,t-1}$ × SCB deposits % $_{c,2010}$	-0.0356***	-0.00801**	-0.0213***	-0.0446***
	(0.0040)	(0.0035)	(0.0082)	(0.0071)
# branches $_{t-1}$	-0.000689***	-0.000304***	-0.00263**	-0.00817***
	(0.00016)	(0.000096)	(0.0012)	(0.0018)
ln(population $_{t-1}$)	-0.000846	0.112***	-0.138	-0.426***
	(0.054)	(0.033)	(0.17)	(0.085)
employment rate $_{c,t}$	-0.0460	0.000827	0.239**	-0.167
	(0.087)	(0.076)	(0.11)	(0.12)
ln(personal income pc $_{c,t-1}$)	-0.517***	-0.313***	-0.433***	-0.576***
	(0.026)	(0.042)	(0.061)	(0.034)
county FE	x	x	x	x
year FE	x	x	x	x
observations	28,084	10,571	5,931	11,582
R-squared	0.221	0.151	0.209	0.273

C Event Studies

I conduct event-study analysis around important improvements in mobile infrastructure. I consider an event window from two years before the event to two years after. I define an event as the county-year pair corresponding to the highest year-on-year % increase in spectrum expansions above 60% for the county. For such county, I then single out 5 untreated (i.e. not belonging to any event window) nearest neighbors the year previous the one of the event based on population, GDP, income per capita. I then exclude the nearest neighbors that witnessed high increases in spectrum expansions around the event. If more than one nearest neighbor remains, I then pick the one with the lowest increase in spectrum expansions the year of the event.

Table C.1: **Event Study: Small Community Bank Branch Closure**

Description: This table presents results of the event study on small community banks' branch closure around high improvements in the local mobile infrastructure ($>60\%$ year-on-year). The event methodology is described in Section 7. The dependent variable is a dummy equal to 1 if there is at least one net small community bank branch closure in county c and year t, 0 otherwise. Only treated and matched control counties enter the estimation. $Treated_{\ c,t}$ is a dummy equal to one if county c is in the event window and witnesses a $>60\%$ year-on-year spectrum expansion increase in the middle of the window. $Post_{\ c,t}$ is a dummy equal to 1 if county c (treated or control) is in the last two years of the event window (post event). Different specifications load different different fixed effects and county-level controls, with cohort defining a treated county and its assigned control throughout the event window. Standard errors are clustered at county level; ***, **, *, $^{+}$ denote 1%, 5%,, 10% and 15% statistical significance.

	at least one net SCB branch closing$_{c,t}$			
	(1)	(2)	(3)	(4)
Treated $_{c,t}$ × Post $_{c,t}$	0.0536*	0.0536**	0.0499*	0.0525**
	(0.028)	(0.022)	(0.028)	(0.022)
ln(population $_{c,t-1}$)			0.347	-0.464
			(0.42)	(0.50)
ln(# businesses $_{c,t-1}$)			-0.133	0.00251
			(0.23)	(0.28)
employment rate $_{c,t-1}$			-0.569	-0.803
			(0.72)	(0.80)
ln(personal income pc $_{c,t-1}$)			0.160	0.207
			(0.15)	(0.18)
ln(county GDP $_{c,t-1}$)			-0.161**	-0.193*
			(0.080)	(0.099)
county FE	x		x	
time FE	x		x	
cohort FE	x		x	
cohort x time FE		x		x
cohort x county FE		x		x
observations	4,600	4,600	4,600	4,600
R-squared	0.281	0.656	0.283	0.658

Figure C.1: **Event Study: Small Community Bank Branch Closure**

Description: This figure plots coefficients of the $Treated_{\ c,t} \times Post_{\ c,t}$ interaction variable in previous table's specification across the years in the event window, with the year before the event as baseline. Coefficients of treated counties are reported in red, of control counties in blue.

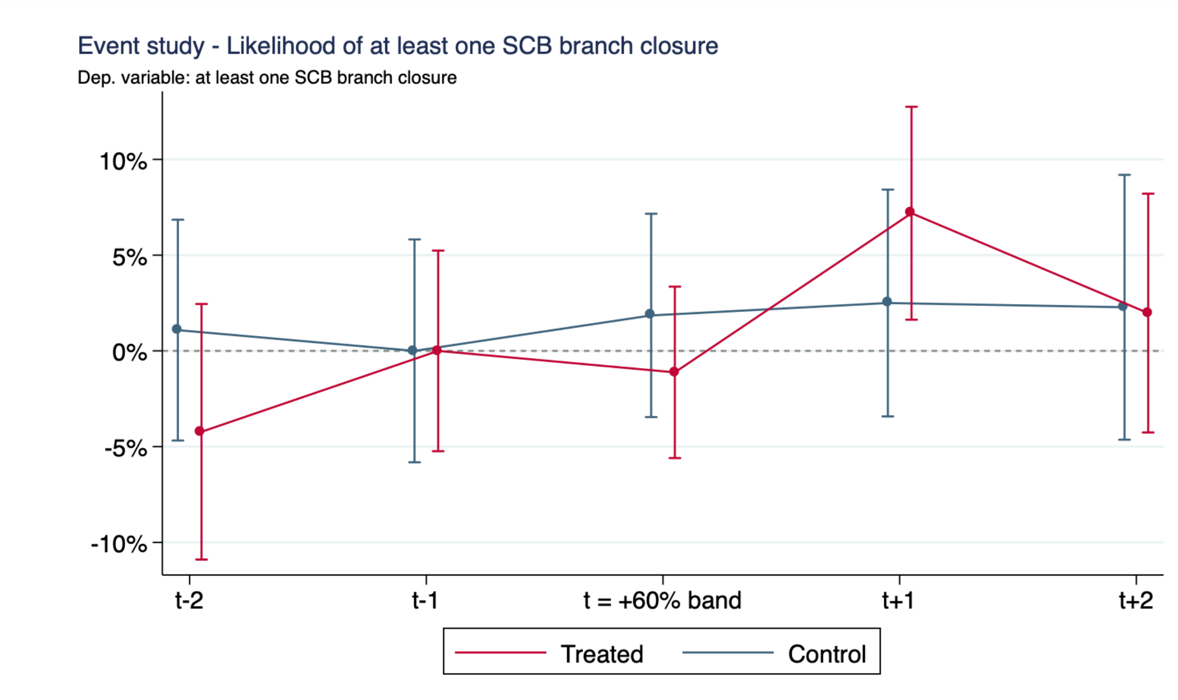


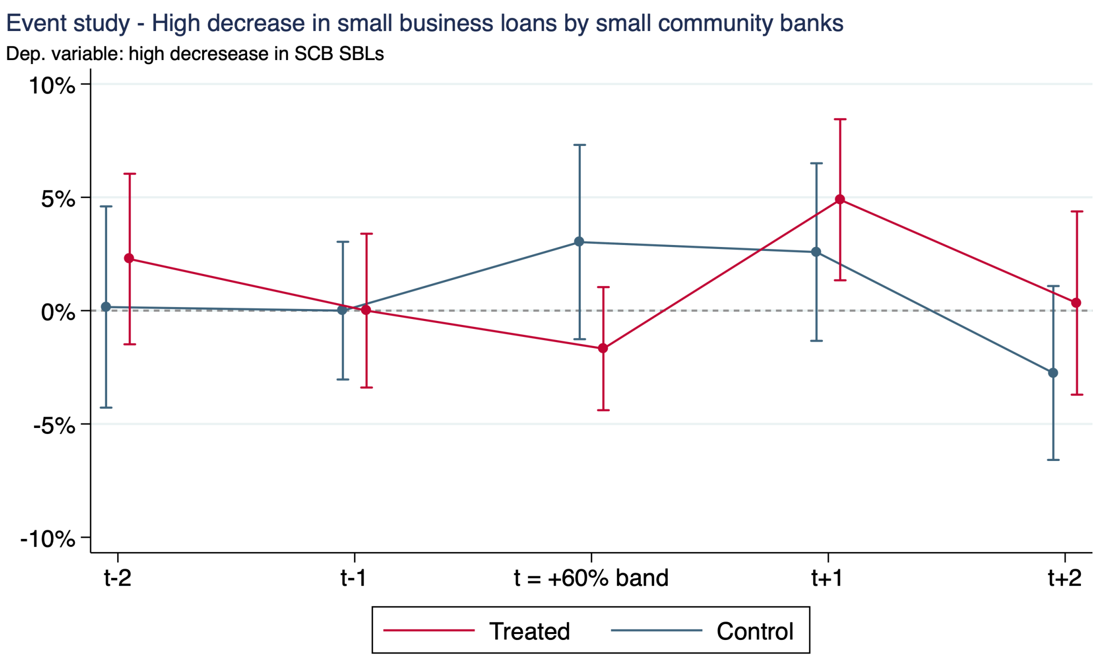
Table C.2: **Event Study: Small Community Bank Small Business Lending**

Description: This table presents results of the event study on small community banks' small business lending around high improvements in the local mobile infrastructure (> 60% year-on-year). The event methodology is described in Section 7. The dependent variable is a dummy equal to 1 if there is a year-on-year decrease of at least 60% in small community banks' small business lending in county c and year t (*high decrease*), 0 otherwise. Only treated and matched control counties enter the estimation. $Treated_{\ c,t}$ is a dummy equal to one if county c is in the event window and witnesses a > 60% year-on-year spectrum expansion increase in the middle of the window. $Post_{\ c,t}$ is a dummy equal to 1 if county c (treated or control) is in the last two years of the event window (post event). Different specifications load different different fixed effects and county-level controls, with cohort defining a treated county and its assigned control throughout the event window. Standard errors are clustered at county level; ***, **, *, + denote 1%, 5%,, 10% and 15% statistical significance.

	high decrease in SCB small business lending $_{c,t}$			
	(1)	(2)	(3)	(4)
Treated $_{c,t}$ × Post $_{c,t}$	0.0368**	0.0368**	0.0357*	0.0353**
	(0.019)	(0.016)	(0.019)	(0.015)
ln(population $_{c,t-1}$)			-0.0808	-0.254
			(0.31)	(0.44)
ln(# small businesses $_{c,t-1}$)			0.279	0.117
			(0.18)	(0.25)
employment rate $_{c,t-1}$			-0.301	-0.988*
			(0.37)	(0.58)
ln(personal income pc $_{c,t-1}$)			-0.0917	-0.103
			(0.12)	(0.13)
ln(county GDP $_{c,t-1}$)			0.0581	0.0840
			(0.070)	(0.073)
county FE	x		x	
time FE	x		x	
cohort FE	x		x	
cohort x time FE		x		x
cohort x county FE		x		x
observations	3,530	3,530	3,529	3,528
R-squared	0.216	0.611	0.217	0.612

Figure C.2: **Event Study: Small Community Bank Small Business Lending**

Description: This figure plots coefficients of the $Treated_{c,t} \times Post_{c,t}$ interaction variable in previous table's specification across the years in the event window, with the year before the event as baseline. Coefficients of treated counties are reported in red, of control counties in blue.



D IV analysis

Following previous literature, I build an instrument for spectrum expansions based on lightning strike frequency.

I rely on National Lightning Detection Network data to get the number of cloud-to-ground lightning strikes in each county each year. I then construct a dummy equal to one if the county's average frequency of lightning strikes across 2010 to 2019 is above sample median. As this measure is however time-invariant, in the following analysis I reduce all other variables in the regressions to their average across 2015 to 2018, the peak of mobile spectrum expansions in the data.

Table D.1: **IV Analysis: Small Community Bank Branches Evolution**

Description: This table presents IV analysis on small community banks' branch closure around following improvements in the local mobile infrastructure. The IV methodology is described in Section 7. *Above med. lightning strikes* $_c$ is a dummy equal to one if the county's average frequency of lightning strikes across 2010 to 2019 is above sample median. It is used as an instrument for spectrum expansions in the first stage (Column 1). As it is time-invariant, all other variables enter the regressions as their average across 2015 to 2018, the peak of spectrum expansions. The dependent variable in Column 2 (second stage) is a dummy equal to 1 if there is at least one net small community bank branch closure in county c between 2015 and 2018, 0 otherwise. The dependent variable in Column 2 (second stage) is a dummy equal to 1 if there is at least one net small community bank branch opening in county c between 2015 and 2018, 0 otherwise. Standard errors are clustered at county level; ***, **, *, $^{+}$ denote 1%, 5%,, 10% and 15% statistical significance.

	spectrum expansions $_c$	at least one net closing $_c$	at least one net opening $_c$
	(1)	(2)	(3)
above med. lightning strikes $_c$	-0.0719***		
	(0.0106)		
$\widehat{\textit{spectrum expansions}}$ $_c$		0.479**	-0.405**
		(0.23)	(0.19)
# branches $_c$	0.0012*	0.00724***	0.00140
	(0.0007)	(0.0011)	(0.00088)
ln(population $_c$)	0.0641***	-0.0223	0.0355
	(0.0228)	(0.041)	(0.033)
ln(# businesses $_c$)	-0.0177	0.0733**	0.0740***
	(0.0218)	(0.035)	(0.028)
employment rate $_c$	0.6484***	-0.524**	0.384**
	(0.1043)	(0.23)	(0.19)
ln(personal income pc $_c$)	0.0576	0.00951	0.0233
	(0.0373)	(0.061)	(0.050)
ln(county GDP $_c$)	-0.0445***	0.0421	-0.0449**
	(0.0150)	(0.027)	(0.021)
observations	2,783	2,783	2,783
R-squared	0.0493	0.0935	-

Table D.2: **IV Analysis: Small Community Bank Small Business Lending**

Description: This table presents IV analysis on small community banks' branch closure around following improvements in the local mobile infrastructure. The IV methodology is described in Section 7. *Above med. lightning strikes* $_c$ is a dummy equal to one if the county's average frequency of lightning strikes across 2010 to 2019 is above sample median. It is used as an instrument for spectrum expansions in the first stage (Column 1). As it is time-invariant, all other variables enter the regressions as their average across 2015 to 2018, the peak of spectrum expansions. The dependent variable in Column 2 (second stage) is the average amount of small community banks' small business lending in county c between 2015 and 2018. Standard errors are clustered at county level; ***, **, *, $^{+}$ denote 1%, 5%,, 10% and 15% statistical significance.

	spectrum expansions $_c$	ln(C&I loans $<$ 1 mill. $_c$)
	(1)	(2)
above med. lightning strikes $_c$	-0.0855***	
	(0.0121)	
$\widehat{spectrum\ expansions}$ $_c$		-3.222***
		(0.81)
# branches $_c$	0.0006	0.0747***
	(0.0010)	(0.0055)
ln(population $_c$)	0.0613**	-0.443**
	(0.0283)	(0.17)
ln(# businesses $_c$)	-0.0143	0.536***
	(0.0268)	(0.15)
employment rate $_c$	0.6587***	3.020***
	(0.1258)	(0.93)
ln(personal income pc $_c$)	0.0791*	-0.425
	(0.0446)	(0.27)
ln(county GDP $_c$)	-0.0482***	0.106
	(0.0185)	(0.11)
observations	2,059	2,059
R-squared	0.0597	-