Keeping Up in the Digital Era:

How Mobile Technology Is Reshaping the Banking Sector

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Abstract

I hand-collect data on the roll-out of mobile banking apps in the U.S. over the previous decade and pair them with local, positive shocks to the importance of mobile services derived by interacting nationwide Federal Communication Commission mobile infrastructure improvement policies with counties' pre-existing share of mobile contracts. I find increased local competition among banks around these shocks, with poorly digitalized small community banks (SCBs) losing deposits and small business lending to larger, better-digitalized banks (LBs). I further provide evidence that these LBs are substituting the traditional branch- and relationship-based lending model of SCBs with digital tools. However, it is not a one-to-one transition.

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

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1 Introduction

Most of the early literature on financial services digitalization emphasized the rise of fintech firms and the competition they externally pose *to* traditional commercial banks (e.g., Buchak et al. (2018), Gopal and Schnabl (2022), Erel and Liebersohn (2020), Berg et al. (2021)). The literature has shifted focus towards the impact digitalization has had *within* the traditional commercial banking sector only recently, in relation to the period of monetary tightening that started in 2022 and the subsequent 2023 banking crisis (e.g., Erel et al. (2023), Benmelech et al. (2023), Cookson et al. (2023)). This paper belongs to this second research stream in nature, but abstracts from the most recent economic developments to investigate instead how the gradual introduction of financial services digitalization in the traditional banking sector over the previous decade has transformed local competition across banks and their lending dynamics.

Throughout, the paper employs hand-collected information on banks' mobile app availability and quality, paired with a novel positive shock to the local importance and popularity of mobile apps. Analysis based on these new data shows that small community banks (assets below $1bn) have been slow to provide mobile banking apps of quality to their customers. As a result, they lose deposits and perspective growth to larger and better-digitalized banks present nearby when the positive shock to app importance hits their geography. On the asset side of their balance sheet, these dynamics translate into a significant decrease in small enterprise lending.[1] Conversely, larger banks increase their small enterprise lending, but only in areas where they do not operate branches, provided that they have mobile banking apps, while fintech firms respond only in urban areas. Ultimately, local economic analysis suggests that these other agents and their more digital lending approaches are not fully able to bridge the gap left by small community banks in the small enterprise lending market.

[1]Small enterprise lending is defined as the sum of small business lending and farm lending.

To the best of my knowledge, this is the first paper to collect data on mobile technology adoption in the U.S. banking sector and to pair such data with a novel local shock to the importance of mobile apps, keeping the analysis in reduced form throughout. In particular, I hand-collect information on the date each FDIC-insured depository institution launched its first consumer banking application from an app analytics platform. I am further able to retrieve the entire update history of each bank's latest app. These new data allow me to track if a bank provides mobile banking services and what their quality is based on how frequently they are updated.

In the first part of the paper, I use this information to investigate mobile technology adoption across banks, its timing, and how it relates to deposits. With the help of parametric survival models, I find that banks adopt mobile technology earlier when their customer base is young and educated and that measures of recent bank performance do not seem to matter. In contrast, the *bank type*—a categorization I introduce based on the geographical reach, size, and scope of operations of the bank—plays an important role in the timing of mobile technology adoption. *Big community banks* (assets above $1bn, yet local reach), *large banks* (assets above $1bn, regional/national reach), and the *big 4 banks* (Bank of America, Chase, Citi, Wells Fargo) introduce mobile banking services much faster than *small community banks* (assets below $1bn, local reach). App update frequency dynamics also suggest that the apps of small community banks are, on average, of lower quality. Importantly, app availability significantly correlates with higher bank-year deposits, hinting at a potential surge in deposit competition across banks with the advent of mobile technology.

At this point, I introduce positive shocks to the value of existing mobile banking apps across geographies to better study local bank competition dynamics. These county-year-level shocks build on the fact that Mobile Network Operators (MNOs—AT&T, T-Mobile, and the like) need frequencies of the electromagnetic spectrum to satisfy the data needs of their customers for communication. These frequencies are allotted by the Federal Communication Commission (FCC) through a licensing system. In particular, during the 2010-2019 timeframe, the FCC has held three big license auctions to cater to the ever-growing data needs of the smartphone and streaming/social media era. Significant amounts of newly available electromagnetic spectrum frequencies have been licensed country-wide to MNOs in these three auctions. My county-year shock variable is, therefore, the interaction between these nation-wide increases in available mobile frequencies and each county's pre-existing share of households with mobile contracts, building on the idea that MNOs would be better equipped for a faster increase in data transfer capacity in areas where they already have a dense presence and infrastructure. This increased mobile data capacity in the county then also increases the value of local pre-existing apps by allowing them to run smoother, develop further in-app services, and ultimately get more users on board. Unfortunately, data on the share of households with mobile contracts are only available from 2013 onwards and for counties with more than 65,000 residents, so the following results are limited in this sense.

I find that when the positive shock to mobile apps' importance hits, institutions operating in the county but not providing mobile banking services lose deposits. In contrast, institutions already operating and offering such services in the county experience significant deposit inflows. The increase in deposits at these so-called digitalized banks is greater if the bank is amongst the county's early mobile technology adopters and keeps updating its app over time. Additional analysis by bank type shows that the gain in deposits after the shock is the largest for big 4 banks with an app, followed by large banks with an app and big community banks with an app, while a small community bank app does not lead to more deposits per se. I analyze deposit pricing and branching dynamics as well. While competition on deposit rates intensifies following county-year shocks to mobile apps' importance, digitalized banks are able to maintain, on average, lower ones. On the branching side, there's a higher likelihood of small community bank branch closures following the county-year shock, especially if small community banks are not digitalized.

These results suggest that mobile technology is acting as a *de facto* negative shock to the deposit franchise of small community banks. Note that deposits play a crucial role at small community banks: they are the base of the close relationships with customers these banks are known for (Berger and Udell (2002), Carter and McNulty (2005)), and constitute both a source of information (Agarwal and Hauswald (2010), Li et al. (2023), Yang (2022)) and of stable funding (Drechsler et al. (2017), Li et al. (2023)) for their lending activities. Therefore, I shift my focus to the asset side of these banks' balance sheets to analyze potential consequences.

In the process, to have a more complete view as the analysis narrows its focus to just one bank type, I set off to reconstruct the total amount of spectrum frequencies accumulated over time by MNOs in each county since 2010. I derive this information by extensively analyzing the entire universe of spectrum licenses made available by the FCC. These extended data include the three big nation-wide frequencies auctions I used to construct the previous local mobile apps' importance shock measure, but also factor in other minor auctions (derived from repurposing local TV and local radio frequencies to local mobile communications). As such, this measure can be considered a more detailed and comprehensive version of the previous county-year shock, and I show that previous results also stand when using it in its place (even when extending to its larger geographical and temporal coverage).

In relation to the asset side of the small community bank balance sheet, I find that a significant increase in local MNOs' data transfer capacity—i.e., around a 100MHz increase in the spectrum frequencies made available to MNOs, which happened twice throughout the sample timeframe—translates into a 15.2% decrease in small community bank small enterprise lending at the county level. Furthermore, small community banks are substituting small enterprise lending with more standardized and less informationally intensive products like mortgages, and the effects are not as strong at small community banks that do provide a mobile banking app.

In light of these findings, I proceed to investigate whether other players fill this small enterprise lending gap. As previously mentioned, unlike small community banks, larger and better-digitalized banks benefit from the mobile technology shock in terms of deposits. However, I find that they increase their small enterprise lending only in areas where they do not operate branches and only if they provide mobile banking services. This result suggests that the introduction of mobile technology is producing a geographical decoupling of small enterprise loan funding (deposits collected through a local branch) and origination (further away from the branch, with the help of technology) at these better-digitalized banks. Fintech firms also contribute, but almost exclusively in metropolitan areas.

I conclude by regressing various measures of local economic and small enterprises' growth on the interaction between the increases in local MNOs' data transfer capacity and the local share of small community bank deposits at the start of the sample. Whereas increases in local mobile infrastructure capacity alone display positive and significant coefficients across specifications, the interaction term displays negative and significant ones. In other words, local businesses and the local economy seem to benefit less from digitalization in areas where small community banks had an important presence before its advent. Further, this outcome points to the more digital lending ways of larger banks and fintech firms not being able to fully substitute for the branch-based lending model of small community banks when it comes to small enterprise funding. The last section then wraps up with robustness checks on the main results just exposed.

Overall, the paper starts from a local bank competition setting paired with mobile technology data to shed light on how the traditional bank business model is navigating great technological progress and on the future of relationship lending. Unlike fintech firms, which mainly focus on one service, banks are characterized by the coexistence of deposit-taking activities on one side and lending activities on the other. Thus far, this feature has proven beneficial thanks to the synergies between the two. Norden and Weber (2010), Agarwal and

Hauswald (2010), and Yang (2022) 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. (2023), 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. However, these synergies are proving more fragile in the digital era and ever-evolving.

First, consider the case of small community banks. These institutions have a small enterprise lending advantage based on the close relationship they have with their customers and synergies with their deposit-taking activities (Petersen and Rajan (1994), Berger and Udell (1994), Cole et al. (2004), Berger et al. (2005), and others). Whereas the consensus has been that they can rely on this advantage to remain competitive going forward (DeYoung et al. (2004), Carter and McNulty (2005), Bongini et al. (2007)), this paper points to the opposite. It shows that small community banks reduce just small enterprise lending when they lose deposits to larger and better-digitalized banks. This result suggests that a business model centered on the synergies between deposit-taking and lending is going to be less and less sustainable going forward if the bank is not fully capable of maintaining a stable deposit base by keeping up with competition and consumers' appetite for innovations.

Second, these synergies are themselves evolving as new technologies revolutionize information collection. There is already evidence in the literature that technological progress has introduced new ways to harden soft information and to gain a similar pool of knowledge (Liberti and Petersen (2019), Berg et al. (2020), Huang et al. (2020)). On the other hand, this paper shows that larger, better-digitalized banks and fintech firms seem to alleviate but not fully make up for the loss of small community bank small enterprise lending in the local economy. These entities' more digital ways of reaching consumers and collecting relevant information seem to only partially substitute for small community banks' relationship- and branch-based information collection. In the future, either the gap will close with further technological progress, or markets will have to settle at a lower capacity for this type of lending.

This paper also contributes to the growing literature on financial services digitalization. Initially, the focus of this literature has been on the rise of fintech firms in relation 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 (2022)). More recently, attention has shifted towards financial services digitalization at the bank level. Dante and Makridis (2021) explore patterns in mobile banking usage versus banks' physical presence. Jiang et al. (2023) investigate how banks' technology investments affect approval decisions, pricing, and repayment in mortgages. Erel et al. (2023), Benmelech et al. (2023), and others analyze the role financial technology has played leading up to and during the 2023 banking crisis.

Closer to this paper, Jiang et al. (2022) contemporaneously set up a model of banking competition under digital disruption where only a fraction of banks digitalize (as proxied by their deposits-to-branches ratio). They show that such a competition has a redistributional effect on financial inclusion across consumers, reducing the unbanked rate for the young while increasing it for the elderly. In later work, Koont et al. (2023) and Koont (2023) collect mobile technology adoption data in a similar fashion to this paper. Inspired by the recent Silicon Valley Bank collapse, Koont et al. (2023) explore the role of digital banking on deposit composition and volatility, while Koont (2023) further highlights how digital banking has allowed mid-sized banks to grow faster, increasing the systemic importance of these institutions in the banking sector.

This paper abstracts from demographic and systemic considerations, focusing instead on the local competition and lending dynamics at the core of the traditional bank business model. In this context, it analyzes how the introduction of mobile technology has impacted the relationship between deposit-taking and small business lending, uncovering a shift from the branch-based paradigm that was thought optimal (raising deposits and lending through the branch) to a more digital and geographically decoupled one (raising deposits through a branch yet lending further away with the help of technology), with marked consequences for local economic growth.

2 Data

Whenever feasible from a data availability perspective, 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 FDIC-insured depository institutions in the U.S., relying on FDIC Summary of Deposits data for branch-level information and FFIEC Call Reports data for institution-level information. I employ three other main sets of data described in the following subsections—mobile banking app data, mobile infrastructure data, and small enterprise lending data. Lastly, I derive control variables from data made available by the Census Bureau, the Bureau of Labor Statistics, and the Bureau of Economic Analysis.

2.1 Mobile banking data

I hand-collected data on when each FDIC-insured depository institution started providing mobile banking services through a joint search of the institution's website and a platform of intel for mobile app developers.[2] The platform's proprietary search engine allowed me to manually look up each bank and see the first time it released a consumer banking app. Based on this information, the analysis then employs the variable $\textit{app available}_{b,t}$, which captures whether bank b has an app available in at least one of the two stores (Google Play,

[2] Data.ai is an online platform that provides mobile 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).

App Store) in year t.[3] Additionally, I collected the update history for the latest Google Play and App Store apps made available by the bank at the time of the data collection (2022). These data consist of the complete list of all the updates—the roll-out of a new version of the app—and their timing. The analysis then employs the variable $\textit{app update intensity}_{b,t}$, which is the ratio of the total number of updates rolled-out until year t (on either store) to the years since the launch of the first app of bank b.

2.2 Mobile Infrastructure data

Throughout the analysis, I employ local shocks to the availability and popularity of mobile services based on improvements in the capacity of the local mobile infrastructure. There are two versions of these shocks: $\textit{county-year shock}_{c,t-1}$ in rougher form yet easier derivation, weighing nationwide mobile infrastructure capacity improvements with the local pre-existing coverage of mobile contracts, and $\textit{spectrum expansions}_{c,t-1}$ in a more precise form, derived by computing the actual increase in mobile infrastructure capacity county-by-county through an extensive analysis of Federal Communication Commission license data. Please refer to subsection 4.2.1 and subsection 5/Internet Appendix D for a thorough explanation of these measures' rationale, derivation, and summary statistics.

2.3 Small enterprise lending data

Due to the lack of a detailed public dataset covering all lenders at once, I rely on three different data sources to analyze small enterprise lending patterns. For banks below $1bn in assets (small community banks), I rely on FDIC Call Report balance sheet entries regarding

[3]Especially earlier in the sample, the same institution would launch its Apple app before its Android one. Programmers back then had a harder time developing apps compatible with the large variety of Android smartphones, which were also less popular. This is why, to be conservative, the analysis uses a variable to capture whether the bank has an app available in at least one of the two stores.

commercial and industrial loans below \$1mn and farm loans below \$0.5mn.[4] These data are at the institution level, but since 90% of small community banks have most of their deposits in one county, I can link them to said county with a supposedly small measurement error. For larger banks, I rely on Community Reinvestment Act (CRA) data, which cover originations of small business and farm loans by bank and borrower location.[5] CRA reports are filed yearly and are mandatory for banks with assets above a pre-determined threshold ($\sim$ \$1.1-1.2 billion during my sample period). For fintech lenders, I rely on data courtesy of Gopal and Schnabl (2022). They derive their small business lending information from UCC filings, which routinely register the non-real estate collateral of small business loans. Their data cover secured small business loan originations from 2010 to 2016 alone but include fintech lending.

3 Mobile technology adoption

I start by investigating general trends in mobile banking adoption. Panel A of Figure 1 plots the evolution of the percentage of U.S. banks providing mobile banking services over the 2007(launch of first smartphone)-2019 time frame. It highlights how bank mobile technology adoption has been staggered over time: only 0.3% of U.S. banks already had an app in 2010, versus $\sim$18% by 2013, $\sim$56% by 2016, and $\sim$77% by 2019. Given such high heterogeneity in app adoption, this section then proceeds to discuss and analyze the possible determinants of a bank's mobile technology adoption decision and its timing.

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

[4]Recent industry studies consider this balance-sheet measure a good proxy for small business lending at small banks (e.g., FDIC (2020b)).

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

study, highly educated individuals are also more likely to use mobile banking. Therefore, I investigate whether banks with a younger and highly educated customer base might be prone to faster adoption.

Strictly from the bank's point of view, I focus on profitability and performance as they might affect the ability and willingness to invest in new technology. Another important element could be the type of bank making the decision. Larger banks have an advantage in the upfront investment required to adopt and maintain new technologies. Banks with broader geographical coverage might have an incentive to adopt early—being susceptible to many competitors across different geographies, it might pay off to invest early in the technology and be amongst the first ones to profit once local demand catches up. On the other hand, banks known for their in-person interactions with customers might perceive less value added from introducing this kind of technology in their operations.

To test these dynamics at once, I introduce a new framework that considers banks across these three main dimensions: size, geographical coverage, and scope of operations. According to this framework, depository institutions with total assets below \$1bn are *Small Community Banks (SCBs)*. These institutions have a very narrow geographical reach and are known to be highly reliant on the soft information they gather through repeated, in-person interactions with their customers. *Big Community Banks (BCBs)* is then institutions that did embrace some economies of scale but kept within the boundaries and the modus operandi of the community bank business model (only present in a few metropolitan areas, highly reliant on the community, deposits, and lending). I follow the methodology in FDIC (2012) to identify them.[6] A distinct category is then dedicated to the *Big 4 Banks (B4Bs)*—Bank of America,

[6] According to FDIC (2012), big community banks are banks satisfying the following conditions: (i) total assets above \$1bn, (ii) loans to assets > 33%, (iii) deposits to assets > 50%, (iv) 75 branches at most, (v) number of large metropolitan statistical areas covered < 3, (vi) number of states covered < 4, and (vii) no branches with more than \$ 5 billion in deposits. Such institutions have been shown to contribute to small business lending significantly and to present more community bank-like traits than their larger counterparts (Hughes et al. (2016), Nguyen and Barth (2020)).

Chase, Citi, Wells Fargo. All remaining depository institutions fall into the residual category of *Large Banks (LBs)*—banks with assets above \$1bn and regional/national coverage, known to be highly reliant on hard information in their decision-making processes and to maintain a transactional approach with their customers. Panel A of Table 1 reports summary statistics for each bank type.

I employ survival analysis on the newly hand-collected data on mobile technology adoption to investigate whether these elements influence the bank's timing in launching its first mobile app over the 2007-2019 timeframe. Panel A of Table 2 presents hazard ratios from a parametric survival model where the patient is the bank and the end event is the launch/adoption of the app.[7] The model captures whether each of the above elements results in quicker or slower app adoption—hazard ratios above one representing quicker app adoption and below one slower adoption. Estimates show that an older customer base slows app adoption, whereas a highly educated one speeds it up.[8] Further, big community banks, large banks, and big 4 banks are much faster than small community banks in adopting mobile banking technology. Regarding bank performance measures, ROA (net income over assets) and Net Interest Margin (net interest income over assets) present coefficients greater than one but not significant. A higher Tier 1 Leverage Capital Ratio slows app adoption, highlighting a potential tradeoff between capitalization and financing innovation.

Having assessed these trends, the following linear regression model in Panel B of Table 2 then serves as an additional test at the year-county-level, where the demographic and local banking variables are more precisely identified:

$$\begin{aligned} \%\ \textit{branches providing app}_{c,t} = \alpha_s + \alpha_t + \beta_1\ \textit{county demographics}_c + \\ \beta_2\ \textit{bank type presence}_{c,t} + \epsilon_{c,t}, \quad (1) \end{aligned}$$

[7]The model is calibrated on a Weibull survival distribution since the likelihood of getting an app increases over time as the technology improves and these services become more and more popular.

[8]A deposit-weighted average of the percentage of people ages 65 and older/with higher education across the counties the bank operates in proxies for customer base age/education dynamics.

where the dependent variable $\%$ *branches providing* $app_{c,t}$ is the percentage of county c year t branches that belong to banks that provide a mobile banking app. Among the independent variables, *county demographics*$_c$ include the share of county population ages 65 and older and the share of county population that received higher education (as per 2010 Census), and *bank type presence*$_{c,t}$ are dummies for the presence of at least one big community bank, large bank, and big 4 bank branch in the county ($I(big\ comm.\ bank\ branches_{c,t})$, $I(large\ bank\ branches_{c,t})$, and $I(big4\ bank\ branches_{c,t})$, respectively). The specification includes state fixed effects α_s and year fixed effects α_t.

Column 1 in Panel B of Table 2 shows that 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 5.9% with respect to the unconditional sample mean (41.07%). At the same time, a one-standard deviation increase in the share of the highly educated population (7.31%) increases the % branches providing an app in the county by 7% with respect to the unconditional sample mean. In column 2, adding the bank-type presence dummies to the specification increases the within-R-square from 3.55% to 12%. Having a big 4 bank in the county raises the local percentage of branches that provide mobile banking apps by 26.05% with respect to the unconditional sample mean. Having a large or big community bank in the county raises the local percentage of branches that provide mobile banking apps by 19.72% and 10%, respectively. Columns 3 and 4 repeat the analysis with the percentage of deposits held at banks that provide mobile banking services as the dependent variable. Patterns are similar.

Overall, estimates point to banks considering customer age and education in their mobile technology adoption decision, but also to bank type being a crucial component in timely app adoption. The bottom-left plot in Figure 1 displays the evolution of the percentage of banks providing an app over time within each bank-type category and further confirms that small community banks have consistently trailed behind the other three bank types in providing mobile banking services. Interestingly, big community banks—operating a similar business model but on a larger scale—are faring digitalization well. Big 4 banks have been at the forefront of digitalization throughout, while large banks fared well at first and then slowed down.[9] The bottom-right plot of Figure 1 shows how small community bank apps also average the lowest app update rates among all bank types.

These dynamics align with survey work conducted by the FDIC, where small community banks emerge as challenged in the adoption of new technologies, especially on the cost side (FDIC (2020a)). Another element contributing to these patterns could be the scope of small community banks' operations. These banks are known for their close client relationships, built through repeated human interaction. They might not foresee their clients' desire for digital services or miscalculate their importance. The next section will build on these dynamics and investigate their impact on bank competition.

4 Technology-spurred competition on deposits

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 (2022)). In response, commercial banks have also been increasing their digital footprint. One obvious way they have been doing so is by offering mobile banking services to their customers. This section aims to understand whether providing such services led them to compete with each other on one additional dimension that was previously absent. In particular, I will be analyzing deposit patterns across banks in relation to the provision and quality of their mobile banking services. Subsection 1 presents bank-level evidence that having a banking app is linked with

[9] This pattern is likely due to the residual nature of the category. It contains sizable national banks that have been early adopters (initial high levels of app adoption), as well as foreign banks and institutions that mainly provide wealth-management services and have less use for commercial banking apps (subsequent slack).

higher deposits; subsection 2 introduces a county-year shock to the importance of these apps to establish a more causal link.

4.1 Mobile technology and deposits, bank level

I start by investigating bank-level deposit patterns around the introduction of mobile banking services. I employ bank-level data from Call Reports and my newly hand-collected data on mobile banking services over the 2007-2019 sample. I acknowledge the endogeneity of the decision to start providing mobile banking services highlighted in the previous section. Therefore, I employ the following two-way fixed effect difference-in-differences model mainly to analyze general patterns:

$$ln(deposits_{b,t}) = \alpha_b + \alpha_t + \beta_1 \ app \ available_{b,t-1} + \gamma X_{b,t-1} + \epsilon_{b,t} \quad (2)$$

where $ln(deposits_{b,t})$ is the natural logarithm of deposits of bank b in year t, 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 time t-1. α_b represent bank fixed effects, and α_t are year fixed effects. $X_{b,t-1}$ is a set of lagged bank-year controls that includes ROA (net income over assets), net interest margin (net interest income over assets), tier 1 leverage capital ratio, and the number of counties the bank has at least one branch in.

Table 3, Column 1 shows how providing an app increases deposits by 9.44%. Including the aforementioned controls lowers the coefficient to 8.19% without loss of significance. Column 3 further distinguishes whether the app is from a small community bank (SCB), big community bank (BCB), large bank (LB), or big 4 bank (B4B) according to the framework introduced in the previous section. The 8.19% increase in deposits previously highlighted is an average of a 3.08% increase at SCBs, a 22.70% increase at BCBs, a 45.90% increase at LBs, and a 38.30% increase at B4Bs.

Overall, results suggest that the staggered adoption of mobile technologies in the banking sector might have spurred some competition across banks on deposits. Further, the slower in app adoption and the more behind in app quality the bank is according to its type (in order SCB, BCB, LB and B4B as seen in section 3), the less it appears to benefit from the introduction of mobile banking services.

4.2 Technology-spurred competition on deposits, bank-county level

Having highlighted a potential relationship between bank deposits and mobile banking services availability, I introduce a county-year-level shock to assess whether this relationship indeed results from increased deposit competition across banks due to their different patterns in mobile technology adoption and quality. The county-year shock is a local shock to the usability and popularity of mobile services, which I derive by combining information from nationwide mobile communication policies with the pre-existing county-level percentage of households with a mobile contract. I thoroughly explain the derivation of this shock variable in the next subsection and then use it for the bank competition analysis in the one after.

4.2.1 County-year shock to mobile apps importance

The Federal Communication Commission (FCC) regulates the usage of the *electromagnetic spectrum*, which is the (non-visible) "range of electromagnetic radio frequencies used to transmit sound, data, and video" through devices such as radios, TVs, and smartphones across the country (FCC website). The FCC manages the spectrum through a licensing system, where new licenses are allotted through auctions. In the case of mobile communications, an FCC license guarantees the holding Mobile Network Operator (MNO - AT&T, T-Mobile, and the like) the exclusive use over a set market area of certain frequencies (i.e., the exclusive use of a precise amount of MHz within a certain part of the spectrum dubbed MHz band).[10] The

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

more frequencies/MHz the MNO controls, the more data it can transfer across customers at higher speeds.

Importantly, over the previous decade, the FCC has been freeing and dedicating more and more parts of the spectrum to mobile communications to satiate the constant demand for greater data transfer capacity stemming from the advent of social media and streaming services. In particular, the quadrupling in the amount of spectrum devoted to mobile communications that happened during the 2010s—which allowed us to start using smartphones in the capacity we do today—can be largely attributed to three big FCC auctions in 2014 and 2016.[11] In 2014, for mobile communications, the FCC freed and auctioned out at once nationwide 65 MHz in the new AWS-3 band of the electromagnetic spectrum, as well as 10 MHz in the new H Block band. In 2016, it further auctioned out nationwide another 70 MHz of frequencies in the new 600 MHz band. All these licenses were allotted, meaning that in every market area of the country, an MNO bid and won the right to the exclusive use of those frequencies. The bids in these auctions were an historical high, signaling how important it was for MNOs to obtain these licenses to keep up with consumer demand for more mobile data. These three auctions weren't the only ones that happened over the previous decade, but they were the largest in terms of both MHz (70+ each year) and geographical coverage (nationwide).[12]

I build my county-year shock to the better usability and growing popularity of mobile services by interacting the cumulative nationwide MHz increases from these auctions (divided by 100 for readability of results) with the previous year's percentage of households with mobile contracts at the county level. The idea is that in areas where a large share of the local population already uses a smartphone under a mobile contract, the physical infrastructure should be more developed and require less work to exploit the additional frequencies. I

[11]Source: FCC Auctions Summary, contacts in the industry, and anecdotal evidence.

[12]Other minor auctions were staggered throughout, involving lower amounts of MHz on limited geographies by way of repurposing other frequencies previously devoted to local radio and TV.

get information on the share of households with mobile contracts from the Census Bureau's American Community Survey. Unfortunately, the Census started collecting these data in 2013, and only for counties with more than 65,000 residents (around 830 of the overall 3,000+ counties in the US). Therefore, the following analysis will be limited to the 2013-2019 timeframe and to largely populated counties.

Ultimately, the variable *county-year shock*$_{c,t-1}$ can be easily derived, and proxies for an increase in the local usability and popularity of mobile services thanks to the improved local mobile infrastructure capacity it captures. Table 1 provides summary statistics. As expected, it was 0 in 2013 and then progressively increased with marked jumps around 2014 and 2016. For future reference, its standard deviation across the entire sample is 0.42.

4.2.2 Technology-spurred competition on deposits, bank-county level

In this section, I investigate whether there is increased competition on deposits and mobile technology in counties that experience a positive shock to the usability and popularity of mobile services. I employ the county-year shock introduced in the previous section and analyze local deposit flows, pricing, and branch dynamics across banks around it.

Deposit flows. I start analyzing deposit flows using the following baseline regression, which adds a geographic stratum to the data and a double interaction with respect to the previous regression on mobile technology and deposits at the bank level (eq. 2):

$$\begin{aligned} \textit{outcome variable}_{b,c,t} &= \alpha_b + \alpha_c + \alpha_t + \beta_1 \textit{ county-year shock}_{c,t-1} + \beta_2 \textit{ app available}_{b,t-1} \\ &+ \beta_3 \textit{ app available}_{b,t-1} * \textit{county-year shock}_{c,t-1} + \gamma X_{b,c,t-1} + \epsilon_{b,c,t}, \quad (3) \end{aligned}$$

where *outcome variable*$_{b,c,t}$ is the natural logarithm of deposits of bank b in county c and year t, *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 during the entire year t-1, and *county-year shock*$_{c,t-1}$ proxies for increased usability and popularity of mobile services in county c and year t (based on the speed of local implementation of nationwide improvements in mobile infrastructure capacity as per section 4.2.1). α_b represent bank fixed effects, α_c and α_t are county and time fixed effects, and $X_{b,c,t-1}$ is a set of lagged county-year and bank-year controls. County-year controls include population, GDP, income per capita, employment rate, and the number of large and small businesses. Bank-year controls include the number of bank b branches in the county, ROA, the net interest margin ratio, and the tier 1 leverage capital ratio. This specification aims to capture whether banks providing mobile banking services get more deposits compared to other local competitors that do not provide such services when the overall usability and popularity of mobile services increases.

Panel A of Table 4 reports regression estimates. Column 1 suggests that a one standard deviation increase in the county-year shock the previous year translates into a 3.58% decrease in county deposits at banks that did not provide mobile banking services at the time of the increase (as highlighted by the standalone coefficient on $county - year\ shock_{c,t-1}$; -0.0852*0.42 = -0.0358). Banks already providing mobile banking services at the time of the increase witness instead a 1.59% increase in deposits (as highlighted by the coefficient on *county-year shock*$_{c,t-1}$ and the coefficient on the interaction term with app availability; -0.0852*0.42 + 0.123*0.42*1 = 0.0159). Interestingly, the standalone coefficient on *app available*$_{b,t-1}$ is negative and significant, suggesting that app adoption leads the bank to lose deposits within its counties over time instead.

Column 2 investigates this last result by distinguishing whether or not the bank is a late adopter of mobile banking technology compared to the other banks operating within the county. It introduces *app available (early/late adopter in county)*$_{b,c,t-1}$, a dummy variable that takes the value of 1 if bank b provides mobile banking services at time t-1 and if its mobile technology adoption year is below/above the median when looking at the distribution of the adoption years of all the banks operating in county c at time t-1. Estimates in column 2 highlight how the significance of the negative standalone coefficient on *app available*$_{b,t-1}$ in column 1 is mostly driven by the (near) significance of *app available* (*late adopter in county*)$_{b,c,t-1}$ (p-value of 0.14 *vs* p-value of 0.742 for its early adopter counterpart). Furthermore, the coefficient on the interaction term between the county-year shock and *app available* (*early adopter in county*)$_{b,c,t-1}$ is larger and more significant than its counterpart for late adopters. Therefore, column 2 suggests that early adopters in the county reap more benefits from a local positive shock to the usability and popularity of mobile services. In contrast, late mobile technology adopters might already be on a downward trend, which technology adoption and increased popularity of mobile apps can only alleviate.

Regarding robustness, column 3 introduces county x year fixed effects, and column 4 adds a mobile banking services quality angle. Column 3 shows an increase in deposits at banks already providing mobile banking services when the county-year shock hits, even when controlling for local time-varying demand. Column 4 further interacts the app availability x county-year shock variable with a rolling average of the number of yearly app updates by the bank (*app updates intensity*$_{b,t-1}$). Unfortunately, I was able to collect the update history of only the most recent apps for each bank, resulting in a reduced sample size for this specification.[13] Nonetheless, estimates highlight how it is mostly banks that frequently roll out updates that gain deposits during a positive shock to the usability and popularity of mobile services (positive and significant coefficient for *county-year shock*$_{c,t-1}$ x *app updates intensity*$_{b,t-1}$). This result suggests that maintaining high app quality through frequent updates is also an important factor, in addition to timely app adoption.

Panel B of 4 further delves into the adoption timing and quality aspect, maintaining full sample size. It does so by distinguishing whether the app is from a small community

[13] In other words, I do not have the full update history of a bank if the bank has entirely replaced its app at least once, and I have to exclude these cases from the sample).

bank (SCB), big community bank (BCB), large bank (LB), or big 4 bank (B4B)—figure 1 and section 4.1 having shown that the bank type is directly correlated with app quality and deposit competition. Hence, column 1 of Panel B replicates Column 1 of Panel A with the additional bank type distinction. Estimates show that the standalone coefficient on *county-year* $shock_{c,t-1}$ (representing what happens at banks that do not provide mobile banking services when the local usability and popularity of mobile services increases) is still negative, albeit slightly less significant. Further, B4Bs reap the most benefits from a positive shock to the usability and popularity of mobile services (a one standard deviation increase in *county-year* $shock_{c,t-1}$ leads to 7.93% more deposits in the county), followed by LBs (2.59% more deposits), then BCBs (0.81% more deposits). Interestingly, SCBs do not seem able to benefit at all, with the interaction term far from being significant.

For robustness, column 2 adds bank type x year fixed effects and column 3 county x year fixed effects. Controlling for time-varying regulation trends by bank type through the bank type x year fixed effects increases the significance and magnitude of the standalone coefficient on *county-year* $shock_{c,t-1}$, as well as seems to favor B4Bs in reaping off the most benefits from an increase in competition on technology. Controlling for time-varying local demand through county x year fixed effects does not seem to impact results. Lastly, column 4 further distinguishes whether the bank is an early or a late adopter in the county. Unsurprisingly, across all bank types, the banks that adopted earlier reap the most benefits from a local positive shock to the usability and popularity of mobile services. Further, the negative standalone coefficient on *app* $available_{b,t-1}$ in column 1 of Panel A appears to be fully driven by LBs who adopt late, likely already on a downward trend.

Deposit pricing. Internet Appendix B additionally analyses deposit pricing patterns in counties that experience a positive shock to the usability and popularity of mobile services. It illustrates how better-digitalized, larger banks raise their deposit rates less than poorly-digitalized small community banks around a positive county-year shock to the usability and popularity of mobile services. In other words, banks that are less well-positioned on the digital side try to compensate more with deposit pricing at times of heightened digital competition.

Branching. To conclude the competition analysis, I address branching patterns. So far, the analysis has focused on deposit dynamics at banks that are actively present in the counties that witness a positive digital shock, failing to take into account the effect on branch openings and closures by design. Therefore, I look into dynamics in branching around a positive shock to the usability and popularity of mobile services using the following bank type-county-year level specification:

$$\textit{at least one net closing}_{BT,c,t} = \alpha_c + \alpha_t + \beta_1 \, \textit{county-year shock}_{c,t-1} + \gamma X_{c,t-1} + \epsilon_{BT,c,t} \quad (4)$$

where $\textit{at least one net closing}_{BT,c,t}$ is a dummy variable taking the value of 1 if the number of branches of bank type BT in county c is lower in year t then the previous year (bank type BT following the definition in section 3 of SCB or BCB or LB or B4B), and $\textit{county-year shock}_{c,t-1}$ proxies for increased usability and popularity of mobile services in county c and year t (as per section 4.2.1). α_c and α_t are county and time fixed effects, and $X_{c,t-1}$ is a set of lagged county-year that include population, GDP, income per capita, employment rate, and the number of large and small businesses.

Table 5 reports regression estimates. The first three columns consider the full sample, while the fourth and last column excludes from the count in $\textit{at least one net closing}_{BT,c,t}$ those branch closings that are the result of an acquisition from a bank of a different bank type.[14] Column 1 shows that a one-standard deviation increase in $\textit{county-year shock}_{c,t-1}$

[14]Whereas if a branch is acquired by a bank of the same bank type, $\textit{at least one net closing}_{BT,c,t}$ does not change by construction.

leads to a 9.48% increase in the likelihood of local net SCB branch closures with respect to the unconditional sample mean, as well as a 15.76% decrease in the likelihood of local net BCB branch closures, a 18.89% increase in the likelihood of local net LB branch closures. Column 2 introduces bank type x year FE, controlling for time-varying trends and regulations across bank types. Doing so strengthens the effect of *county-year* $shock_{c,t-1}$ on the likelihood of SCB net branch closures to a nearly tripled economic magnitude of 35.82%, while taking away significance from the effect on the other bank types. Sectorial trends and regulations seem to leave SCBs particularly exposed to negative consequences from increased digital competition from a branching point of view—Internet Appendix C further shows that a one-standard deviation increase in *county-year* $shock_{c,t-1}$ leads to a 49.70% decrease in the likelihood of local net SCB branch openings (Column 2 of table C.1).

Column 3 further investigates the role of the pre-existing stage of digitalization at the time of the county-year shock. It does so by introducing $\%$ *of bank type branches with* $app_{BT,c,t-1}$, the percentage of branches of bank type BT in county c already providing mobile banking services at time $t-1$, in interaction with the county-year shock. The interaction coefficient takes a negative sign for SCB closures while displaying positive signs for BCB and LB closures.[15] This suggests that larger, better-digitalized banks are optimally reducing their branch network thanks to their strong digital presence at the time of the shock, whereas poorly-digitalized SCBs are forced to close by the shock instead. Lastly, column 4 replicates column 2 results in the case when the calculation of *at least one net closing* $_{BT,c,t}$ abstracts from branch opening/closings that happen because of mergers and acquisitions across bank types. Now, a one-standard deviation increase in *county-year* $shock_{c,t-1}$ leads to a 15.79% increase in the likelihood of local net SCB branch closures with respect to the unconditional sample mean. Since SCBs have very few branches, this also translates into a steep increase in the likelihood of a full bank closure.

[15]Since all B4B already had apps early in the sample, the interaction coefficient for them is unavailable.

These results, paired with previous analysis on deposit flows and pricing, suggest that SCBs are sustaining the most damaging consequences from increased local competition on the digital side. Adopting mobile apps late and maintaining them less, they witness deposit outflows, have to decrease their deposit spreads more, and close down at higher rates than their larger, better-digitalized competitors following local positive shock to the usability and popularity of mobile services.

Takeaways. Overall, this section paints a picture where, indeed, there is technology-spurred competition amongst traditional commercial banks themselves. In the case of mobile technology analyzed here, this competition stems from the two main elements of the timing of app adoption (the earlier, the better) and the quality of the adopted app (the more updates, the better). Further, bank type seems an important player in these two elements, with SCBs employing more time to adopt an app and producing apps of lower quality compared to BCBs, LBs, and B4Bs. Banks that adopt early and maintain apps of higher quality (mostly B4Bs, LBs) enjoy increased deposits, relatively lower deposit spreads, and optimal branch management around local positive shocks to the usability and popularity of mobile services. Banks that adopt late and/or maintain apps of lower quality (mostly SCBs) endure deposit outflows and higher deposit spreads and are forced toward branch closures instead.

5 Consequences for small community banks

In contrast to bigger banks, Small Community Banks (SCBs) are known to cultivate relationships with their clients through which they acquire soft information they then efficiently use in their lending decisions (Cole et al. (2004), Carter et al. (2004), Berger et al. (2005), Carter and McNulty (2005)). Such relationships arise from 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)). Recent literature has precisely 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 local economy at large (Yang (2022)). 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. (2023), Drechsler et al. (2021)). It follows that the deposit outflows highlighted in the previous section could also be causing SCBs to lose informational insights and liquidity advantages, hindering their ability to operate in the more informationally-sensitive and unstandardized lending markets. I test this hypothesis using Call Report data containing bank-level balance sheet information on the different types of lending. To assess the impact of the local positive shock to the usability and popularity of mobile services on SCB lending patterns, I take advantage of the fact that more than 90% of SCBs have most of their deposits in one county. I therefore link small community bank b's Call Report data to the county c the bank b has most of its deposits in in year t. Given the limited geographical coverage of SCBs, the measurement error should be minimal. I then estimate the following year-bank-county-level specifications:

$$[LT]\ \textit{over assets}_{b,c,t} = \alpha_b + \alpha_c + \alpha_t + \beta_1\ \textit{county-year shock}_{c,t-1} + \gamma X_{b,c,t-1} + \alpha_c + \epsilon_{b,c,t}, \quad \text{(5a)}$$

$$[LT]\ \textit{over assets}_{b,c,t} = \alpha_b + \alpha_c + \alpha_t + \beta_1\ \textit{spectrum expansions}_{c,t-1} + \gamma X_{b,c,t-1} + \alpha_c + \epsilon_{b,c,t}, \quad \text{(5b)}$$

where the dependent variable is $[LT]\ \textit{over assets}_{b,c,t}$, the share of lending type LT over assets for active SCB b in year t having the majority of its deposits in county c. Lending type LT includes small enterprise lending (commercial and industrial loans below \$1mn plus farm loans below \$0.5mn), real estate lending (mortgages), and individual lending (vehicle loans, student loans, personal loans, etc.). α_b represent bank fixed effects, α_c and α_t are county and time fixed effects, and $X_{b,c,t-1}$ is a set of lagged county-year and bank-year controls. County-year controls include population, GDP, income per capita, employment rate, and the number of large and small businesses. Bank-year controls include the number of bank b branches in the county, ROA, the net interest margin and the tier 1 leverage capital ratios.

In equation 5a, the independent variable of interest is *county-year shock*$_{c,t-1}$. As explained in section 4.2.1, it is computed by interacting the amount of spectrum auctioned out by the Federal Communication Commission nationwide (i.e., country-wide increases in mobile infrastructure capacity) with the pre-existing county-level percentage of household with mobile contracts (i.e., how developed the local infrastructure already is and how fast can it pick up the country-wide increase in capacity). Unfortunately, the American Community Survey has been collecting information on the percentage of households with a mobile contract since 2013 and only for counties with more than 65,000 residents, which results in the restricted geographical and temporal coverage of the sample.

Wanting to dig deeper into lending dynamics by bank type and real effects going forward, I set out to derive a more comprehensive version of the county-year shock to the local importance and popularity of mobile apps. I use the entire universe of FCC spectrum licenses, their geographical coverage, and their activation dates to derive the actual increases in spectrum frequencies devoted to mobile communication in each county since 2010 (in 100s of MHz). These increases include the large nationwide improvements in spectrum availability that the *county-year shock*$_{c,t-1}$ measure was based on, as well as some minor local ones following the repurposing of local radio and local TV frequencies to mobile communications. Internet Appendix D contains a detailed explanation of how the resulting variable *spectrum expansions*$_{c,t-1}$ has been derived and further confirms that previous analysis holds under the new measure as well. By construction, the new variable is not only more extensive in coverage (not limited to highly-populated areas or post-2013) but also more accurate in measurement. Panel C of Table 1 reports descriptive statistics for the variable, and Figure Appendix D.1 maps it out over time.

Panel A of Table 6 reports regression estimates for equations 5a and 5b, with small enterprise (commercial + farm) lending as a share of assets in columns 1-3, real estate loans as a share of assets in columns 4-6, individual loans as a share of assets in columns 7-9. For each lending type, estimates are organized in a way that the first column has $\textit{county-year shock}_{c,t-1}$ as the main independent variable of interest over its full sample (highly-populated counties, 2013-2019), the second column has $\textit{sp. expansions}_{c,t-1}$ as the main independent variable of interest over the subsample in which the previous $\textit{county-year shock}_{c,t-1}$ measure is available, the third one has $\textit{sp. expansions}_{c,t-1}$ as the main independent variable of interest over its full sample (all counties, 2010-2019). This is to keep track of results continuity when moving from the rougher $\textit{county-year shock}_{c,t-1}$ to the more precise $\textit{sp. expansions}_{c,t-1}$ available for more counties on a longer timeframe.
Analyzing at once the coefficients on both $\textit{county-year shock}_{c,t-1}$ and $\textit{spectrum expansions}_{c,t-1}$, active SCBs seem to rebalance their lending portfolio indeed away from the information- and liquidity-sensitive market of small enterprise lending when there is an increase in the local mobile infrastructure capacity (a positive shock to the local importance and popularity of mobile apps). The three coefficients for small enterprise loans are negative and display similar orders of magnitude, albeit the one on $\textit{county-year shock}_{c,t-1}$ is not significant. However, over the same geographies and timeframe, the more comprehensive measure $\textit{sp. expansions}_{c,t-1}$ displays significance. Furthermore, extending the coverage of the sample to include counties with less than 65,000 people and years since 2010 (as allowed by $\textit{sp. expansions}_{c,t-1}$) confirms the results. The remaining columns of the panel provide additional evidence that SCBs seem to rebalance their assets towards more standardized products like mortgages and individual loans. All coefficients on individual loans are positive and mostly significant with similar magnitudes. Coefficients for mortgages diverge across the two measures, but the

more comprehensive measure *spectrum expansions*$_{c,t-1}$ is positive and significant both in the limited and full samples.

Panel B further investigates small enterprise lending in relation to technology-driven competition, with the logarithm of the small enterprise lending amount by bank b in year t linked to the county c with most bank b deposits as the dependent variable. Both columns 1 and 2 display negative coefficients of similar magnitudes, with the more comprehensive measure *spectrum expansions*$_{c,t-1}$ also showing significance. According to column 2, a significant increase in *sp. expansions*$_{c,t-1}$ of 100MHz—similar increases happened about twice for counties throughout the sample timeframe—results in a 10.8% decrease of small enterprise loans on the balance sheet of the SCBs active in the county. Column 3 and 4 introduce an interaction of the independent variable of interest with *app available*$_{b,t-1}$. If it is the deposit outflows at SCBs deriving from technology-driven competition that are prompting a decrease in small enterpriser lending, then SCBs with an app should witness lower (deposit outflows and lower lending) decreases. Indeed, in column 3, the county-year shock alone causes a drop in small enterprise lending (negative and significant coefficient on *county-year shock*$_{c,t}$), but not as steep if the bank has an app (positive and significant coefficient on the interaction with app availability). Column 4 exhibits the same pattern for spectrum expansions, but the interaction term lacks significance. Column 5 illustrates that significance is instead there, at least in areas where SCBs face high competition from larger (better-digitalized) banks.

The analysis so far has focused on active SCBs in a bank-county-year setting, but we know branch closures follow the county-year shocks as well (table 5). Internet Appendix E replicates the analysis on SCBs' small enterprise lending amounts at the county-year level, therefore also incorporating potential fluctuations from branch closures. Table E.1 shows that a significant increase in *sp. expansions*$_{c,t-1}$ of 100MHz—similar increases happened about twice for counties throughout the sample timeframe—results in a 15.2% county-level decrease in the overall amount of small business loans reported on the balance sheet of local SCBs.[16] This effect is economically significant, not just from the point of view of SCBs but for small businesses as well. Gopal and Schnabl (2022) estimate traditional commercial banks to represent around 42.67% of overall small business lending, of which 22.46% by SCBs alone (2016 data). According to these estimates, this paper's 15.2% decrease in small business lending of SCBs 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.

Overall, there is evidence that SCBs suffer from deposit outflows and a decline in small enterprise lending during periods of heightened technological competition spurred by local mobile infrastructure capacity improvements. In light of these results, I proceed to investigate whether other agents make up for the gap left by SCBs in the small enterprise loan market.

6 Consequences for the local economy

Having shown decreased small business lending from small community banks following improvements in local mobile infrastructure capacity (proxying for increased local importance and popularity of mobile apps), I proceed to investigate funding consequences for small enterprises (Section 6.1) and real effects (Section 6.2).

6.1 Small enterprise lending dynamics

In this subsection, I investigate whether other agents take on the gap left by small community banks in small enterprise lending during times of heightened technological competition.

[16]The coefficient on the less comprehensive measure *county-year* $shock_{c,t-1}$ is similarly negative, albeit it does not meet the significance threshold either out of a lack of enough variation or a weaker effect in more populated areas.

Larger banks. I start with larger, better-digitalized banks and test whether they increase their small business lending in counties that experience a positive shock to the usability and popularity of mobile services. In contrast to SCBs, these institutions are known for their transactional approach and 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)). Therefore, it is unclear whether they would pick up much of the small business lending now foregone by SCBs, even under the deposit increases they witness following improvements in the local mobile infrastructure capacity (Table 4).

To analyze small enterprise lending, the previous SCBs-focused section used Call Report data on commercial and industrial loans below \$1mn and farm loans below \$0.5mn (Section 5). However, since Call Report data are only available at the institution level, they cannot be geographically linked to the mobile infrastructure capacity data with sufficient precision in the case of larger banks. For this reason, I use Community Reinvestment Act (henceforth CRA) data in this section instead. CRA data report small business loan and farm loan originations by borrowers' location for banks with assets above a pre-determined threshold, allowing me to link the borrowers' location to the mobile infrastructure capacity data. During my 2010-2019 time frame, the assets' threshold for CRA reporting hovered around \$1.1 billion/\$1.2 billion. Hence, CRA data cover all non-community banks (large banks and big 4) and $\sim$ 75% of the big community banks in my sample. Whereas magnitudes across the following regressions cannot be directly compared with the previous SCB analysis, I should still be able to capture general lending trends through the following year-bank-county-level regressions:

$$ln(lending\ amount_{b,c,t}) = \alpha_c + \alpha_t + \beta_1\ county\text{-}year\ shock_{c,t-1} + \gamma X_{b,c,t-1} + \epsilon_{b,c,t} \tag{6a}$$

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

where $ln(lending\ amount_{b,c,t})$ is the natural logarithm of bank b new small enterprise loans (to businesses and farms) in county c and year t, $county\text{-}year\ shock_{c,t-1}$ captures faster implementation of nationwide mobile infrastructure improvements policies, and $sp.\ expansions_{c,t-1}$ capture actual mobile spectrum expansions since 2010 in county c and year t-1 (in terms of the 100s of MHz of new electromagnetic spectrum that have been allotted to the county's mobile network operators). Then, α_c represent county fixed effects, α_t are year fixed effects, and $X_{b,c,t-1}$ is a set of lagged county-year and bank-year controls.[17]

Panel A of Table 7 presents regression estimates for equations 6a and 6b. Columns 1 to 3 separately analyze small enterprise lending by borrower location in areas where the lending bank does have a branch ("branch-based" lending). Columns 4 to 8 focus on small enterprise lending to borrowers located in areas where the lending bank does not operate branches ("remote/digital" lending). Again, in each of the two cases, estimates are organized in a way that the first column has $county\text{-}year\ shock_{c,t-1}$ as the main independent variable of interest over its full sample (2013-2019, highly populated counties), the second one has $sp.\ expansions_{c,t-1}$ as the main independent variable of interest over the subsample in which the previous $county\text{-}year\ shock_{c,t-1}$ measure is available, the third one has $sp.\ expansions_{c,t-1}$ as the main independent variable of interest over its full sample (2010-2019, all countes) for continuity purposes.

None of the coefficients of interest are consistently significant over the branch-based lending subsample, suggesting local branches of larger banks do not modify their small enterprise lending following the deposit inflows highlighted in table 4. However, the more comprehensive measure $sp.\ expansions_{c,t-1}$ exhibits positive and significant coefficients in columns 5 and 6, suggesting that large banks tend to increase their remote/digital lending instead after local mobile infrastructure capacity improvements. Furthermore, columns 7 and 8 highlight how

[17]County-year controls include population, GDP, income per capita, employment rate, and the number of small businesses. Bank-year controls include the number of bank b branches in the county, ROA, the net interest margin and the tier 1 leverage capital ratios.

it is large banks with an app that solely drive this increase, confirming its more digital nature (positive and significant coefficient on the interaction term between *sp. expansions*$_{c,t-1}$ and *app available*$_{c,t-1}$, even robust to county x year fixed effects).[18]

Overall, larger and better-digitalized banks appear to increase only their remote/digital small business lending following improvements in the local mobile infrastructure. This pattern points to mobile technologies facilitating a geographical decoupling of small enterprise loan funding and origination, whereby following local mobile infrastructure capacity improvements, large banks collect more deposits in areas where they have branches but increase their small business lending only in areas where they don't have branches.

Fintech firms. I then proceed to analyze whether fintech firms also increase their small business lending following mobile infrastructure capacity improvements. For this part of the analysis, I use data courtesy of Gopal and Schnabl (2022) on secured small business loan originations from 2010 to 2016 derived from UCC filings. The data display small business loan origination counts in each county each year by fintech firms, allowing me to 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 Δ *small business loans*$_{c,t,t-1}$ is the number of small business loans granted by fintech firms in county c and year t minus the corresponding number the previous year, and *spectrum expansions*$_{c,t-1}$ capture mobile infrastructure capacity improvements in county c and year t-1 in terms of the 100s of MHz of new electromagnetic spectrum that have been allotted to the county's mobile network operators since 2010. α_c represent county fixed effects, α_t are

[18] The negative and significant standalone coefficient on *app available*$_{c,t-1}$ could be caused by large banks that adopt late in the county, likely already on a downward trend as explained in section 4.2.2.

year fixed effects, and $X_{c,t-1}$ is a set of lagged county-year demographic and end economic controls.[19]

The first column in Panel B of Table 7 shows an increase in overall small business lending from fintech firms following local mobile infrastructure improvements (positive and significant β_1 coefficient). Whereas the rougher county-year shock variable cannot be employed here as it has poor temporal overlap with the fintech lending data, for continuity, column 2 nonetheless restricts to counties with more than 65,000 residents (the condition for county-year shock availability), while column 3 restricts to counties with less than 65,000 residents. Estimates suggest that fintech firms substitute for SCBs only in highly-populated areas.

Takeaways. Overall, this section provides evidence that larger, better-digitalized banks and fintech firms attempt to substitute for small community banks in the small enterprise lending market at times of heightened technological competition.[20] However, the different nature of the data employed in this section does not allow me to draw conclusions on the extent to which digital small enterprise lending at larger banks and fintech firms is able to compensate for the decrease in SCBs' branch-based small enterprise lending. The next section will try to shed light on the actual extent of this compensation by analyzing real effects.

6.2 Real effects

In this section, I use the following specification to investigate whether the decrease in SCBs' small enterprise lending has economic consequences despite the potential offsetting by other, more digital lenders:

[19]County-year controls include the number of bank branches, population, GDP, income per capita, employment rate, and the number of small businesses.

[20]Remotely and in highly populated areas, respectively.

$$growth\ variable_{c,t} = \alpha_c + \alpha_t + \beta_1\ spectrum\ expansions_{c,t-1}$$
$$+ \beta_2\ spectrum\ expansions_{c,t-1} * share\ SCB\ deposits_{c,2010} + \gamma X_{c,t-1} + \epsilon_{c,t}, \quad (8)$$

where the dependent variable $growth\ variable_{c,t}$ is county c year t GDP growth or growth in the number of small businesses (from the Census Bureau's County Business Patterns) or small businesses' employment growth or small businesses' wage growth (based on based Census Bureau's Quarterly Workforce Indicators for companies with less than 50 employees). $Spectrum\ expansions_{c,t-1}$ capture mobile infrastructure capacity improvements in county c and year t-1 in terms of the 100s of MHz of new electromagnetic spectrum that have been allotted to the county's mobile network operators since 2010, and $share\ SCB\ deposits_{c,2010}$ is small community bank 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.[21]

This specification is designed to capture the real effects of the decrease in small business lending by SCBs after local mobile infrastructure capacity improvements separately from the real effects of the improvements themselves. The coefficient of interest is β_2, the interaction between the share of SCB deposits in the county at the sample's start and the local mobile infrastructure capacity improvements. It captures whether the economic effects of mobile infrastructure capacity improvements differ where SCBs had an important presence before their advent. Given the results in the previous section, a negative and significant β_2 coefficient would suggest that the digital lending of larger, better-digitalized banks and fintech firms is not able to fully offset the decrease in branch-based small business lending by SCBs that follows mobile infrastructure capacity improvements.

[21] County-year demographic and economic controls include the number of bank branches, population, GDP, income per capita, and employment rate.

Table 8 presents estimation results. It starts from overall county GDP growth in columns 1 to 3, also reporting results for the *county-year* $shock_{c,t-1}$ and the interim results of *spectrum* $expansions_{c,t-1}$ on the subsample where the county-year shock data are available. Whereas the coefficients on the standalone variables representing local mobile infrastructure capacity improvements are positive and significant, the coefficients on the interaction variable are negative and significant. Estimations in column 3 suggest that a significant increase in *spectrum* $expansions_{c,t-1}$ of 100MHz—similar increases happened about twice for counties throughout the sample timeframe—leads to a 3.9% increase in county GDP growth in the absence of SCBs in the area, but only a 1.9% increase if 53.74% of county deposits were held at SCBs in 2010 (the unconditional sample mean). The average presence of SCBs locally nearly halves the growth gains from digitalization.

Columns 4 to 6 display similar patterns for measures of small business growth. A significant local improvement in mobile infrastructure capacity—100 MHz—translates to a 0.27%, non-significant, and 0.61% increase in the growth of the number of small businesses, their employment growth rate, and wages growth rate, respectively, in the absence of SCBs. However, assuming small community banks served 53.74% of the depositors in the county in 2010 (the sample average back then), counties simultaneously witness a 0.22%, a 0.28%, and a 0.28% decrease in the growth of the number of small businesses, their employment growth rate, and wages growth rate, respectively.[22] Magnitudes appear generally small, but unconditional sample means for the dependent variables are similarly small— -0.07%, 0.28%, and 2.41%, respectively—making the estimates economically significant.

Overall, results suggest that a diffused presence of SCBs before mobile digitalization leads to lower economic gains from it. This finding indirectly confirms the lack of full substitutability between the branch-based small business lending operated by SCBs, which

[22]Number of businesses: 1*0.5374*(-0.00417) = 0.00222. Employment: 1*0.5374*(-0.00526) = 0.00283. Wages: 1*0.5374*(-0.00522) = 0.00281.

decreases after mobile infrastructure capacity improvements, and the more digital lending operated by larger, better-digitalized banks and fintech firms.

7 Robustness

The following subsections contain a series of robustness tests to support the main findings. Subsection 7.1 highlights how results have been consistent across different geographies throughout the analysis. Subsection 7.2 shows deposit competition results remain consistent when a merger externally imposes app adoption. Subsection 7.3 presents event studies around significant improvements in local mobile infrastructure capacity. Subsection 7.4 shows the economic consequences of the technology-spurred competition dynamics highlighted in the paper are stronger for the smaller local businesses. Lastly, subsection 7.5 runs Placebo tests over the most important parts of the analysis by randomizing spectrum expansions within-county over time.

7.1 Geographical distribution of effects

A primary concern in the analysis is the geographical distribution of the highlighted effects. SCBs tend to be weaker in urban areas, where cell phone reception might also be better. Therefore, the analysis might be picking up urban *versus* rural evolutionary patterns rather than the effect of mobile technology adoption. Against this argument, the proxy used for local shocks to the availability and popularity of mobile apps (local improvements in mobile infrastructure capacity) does not display significant differences across rural and urban geographies (see Figure Appendix D.1 for reference). Furthermore, most of the analysis throughout the paper has been run using both the $\textit{county-year shock}_{c,t-1}$ measure and the $\textit{spectrum expansions}_{c,t-1}$ measure, and comparing results (Tables 6 onwards, Internet Appendix D). Recall that the $\textit{county-year shock}_{c,t-1}$ measure is only available for counties with more than 65,000 residents, mainly covering metropolitan areas. In no part of the analysis, coefficients across the two measures have heavily diverged in terms of magnitude, sign, and significance, except when it comes to the small business lending of fintech firms in Panel B of Table 7. Only there, it seems that fintech firms mostly operate in metropolitan areas, whereas in general, results have been consistent when expanding to include counties with less than 65,000 residents (including rural areas). Therefore, there is no empirical evidence that the geographical distribution of banks and mobile infrastructure capacity improvements are the main driving forces behind the paper's results.

7.2 Acquisitions analysis

Much of the analysis in the paper focuses on developments in the banking sector in relation to the different patterns in mobile technology adoption present across banks and over time. However, there could be drivers of the choice of when to adopt the app that might also be causing the highlighted developments by themselves. Internet Appendix F addresses this concern by focusing on when an acquisition externally imposes app adoption. It considers branches that started providing mobile banking services to their customers because they were acquired by banks that were already providing such services to their customers before the acquisition. Arguably, the absence of an app at the acquired branch is not influential in the acquisition decision if the acquisition went through. However, due to the acquisition, the acquired branch finds itself endowed with the technology. The analysis then compares these branches to branches that underwent acquisitions, but the acquirer was not providing mobile banking services to its customers at the time of the acquisition. It restricts the event window from two years before to two years after the acquisition and the sample to branches run by small community banks (as the most likely to get acquired and to have enough branches available in the control group). Based on this subsample, the appendix presents estimates of the following regression:

$$ln(branch\ deposits_{i,b,c,t}) = \alpha_i + \alpha_c + \alpha_t + \beta_1\ spectrum\ expansions_{c,t-1} + \beta_2\ post\ acquisition_{i,b,c,t} +$$
$$\beta_3\ spectrum\ expansions_{c,t-1} * post\ acquisition_{i,b,c,t} + \beta_4\ spectrum\ expansions_{c,t-1} * treated_{i,b,c,t} +$$
$$\beta_5\ post\ acquisition_{i,b,c,t} * treated_{i,b,c,t} + \beta_6\ spectrum\ expansions_{c,t-1} * post\ acquisition_{i,b,c,t} * treated_{i,b,c,t}$$
$$+ \gamma X_{b,c,t-1} + \epsilon_{i,b,c,t} \quad (9)$$

where $ln(branch\ deposits_{i,b,c,t})$ is the natural logarithm of bank b's branch i deposits 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 the 100s of MHz of new electromagnetic spectrum that have been allotted to the county's mobile network operators since 2010. $Treated_{i,b,c,t}$ is a dummy variable equal to one if branch i of bank b in county c and year t is going to or has been acquired by a bank that provides mobile banking services. $Post\ acquisition_{i,b,c,t}$ is a dummy variable equal to one if branch i of bank b in county c and year t has been acquired in year t or t-1 or t-2 by another bank. α_i represent branch fixed effects, α_c are county fixed effects, α_t are year fixed effects, and $X_{b,c,t-1}$ is a set of lagged county-year and bank-year controls.[23]

Table F.1 shows that $spectrum\ expansions_{c,t-1}$ x $post\ acquisition_{i,b,c,t}$ carries a negative and significant coefficient, suggesting an improvement in local mobile infrastructure capacity leads to significant deposit outflows when the branch has been acquired by an institution that does not provide mobile banking services, and therefore remains without an app. The coefficient on $post\ acquisition_{i,b,c,t}$ x $treated_{i,b,c,t}$ is also negative and significant, which could be due to acquisitions by better-digitalized banks entailing more changes at the branch level, and some customers nonetheless opting to leave. On the other hand, the coefficient

[23]County-year controls include population, GDP, income per capita, employment rate, and number of businesses above and below a 100 employees. Bank-year controls include the bank's ROA, net interest margin, and tier 1 level capital ratio.

on *post acquisition*$_{i,b,c,t}$ x *treated*$_{i,b,c,t}$ x *spectrum expansions*$_{c,t-1}$ carries a strongly positive and significant coefficient, suggesting that gaining an app through an acquisition leads to an increase in branch deposits following local mobile infrastructure capacity improvements. Its magnitude also overcomes the direct effect of *post acquisition*$_{i,b,c,t}$ x *treated*$_{i,b,c,t}$, albeit not the joint effect of *post acquisition*$_{i,b,c,t}$ x *treated*$_{i,b,c,t}$ and *spectrum expansions*$_{c,t-1}$ x *post acquisition*$_{i,b,c,t}$. Nonetheless, it confirms the paper's first main finding that deposits increase at banks that provide mobile technology when the local mobile infrastructure improves (Table **??**).

The other main findings in the paper relate mobile technology adoption patterns across banks to deposit pricing and small enterprise lending. Unfortunately, they cannot be explored in an acquisition setting due to data limitations. [24]

7.3 Event study analysis

Internet Appendix G conducts event study analysis around important improvements in mobile infrastructure capacity. It defines an event as the county-year observation corresponding to the highest year-on-year % increase in spectrum expansions above 60% for the county. It considers an event window from two years before the event to two years after. For each event observation, five untreated (i.e., not belonging to any event window) nearest neighbors are singled out based on population, GDP, and income per capita the year before the event. The nearest neighbor with the lowest increase in spectrum expansions is then picked. Because spectrum expansions display an increasing trend everywhere over time (see Table 1 and Figure Appendix D.1 for reference), this matching procedure is critical in pairing high increases (the treatments) to very low ones (the best control options available). For this

[24]Deposit pricing data are only available for the rate-setting branches covered by RateWatch, which have poor overlap with the acquisitions sample. Small enterprise lending data come from Call Reports for small community banks and CRA Reports for larger banks. Given that banks of any size acquire small community bank branches, the analysis would entail comparing small etnerprise data from different sources, which is unfeasible.

reason, whereas the total absence of patterns in the control group is not to be expected, stronger effects should appear in the treatment group.

The first event study tests how SCB branch closure rates respond to important improvements in local mobile infrastructure capacity through the following specification:

$$at\ least\ one\ net\ SCB\ closing_{c,t} = \alpha_c + \alpha_t + \alpha_k + \beta_1\ treated_c * post_t + \gamma X_{c,t-1} + \epsilon_{k,c,t}, \quad (10)$$

where *at least one net SCB 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).[25]

Table G.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 (a $\sim$ 30% increase with respect to the unconditional sample average). Figure G.1 reports changes in interaction coefficients over the event years with respect to the year prior to 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.

The second event study tests whether SCBs decrease their small enterprise lending following important improvements in local mobile infrastructure capacity. It applies the same procedure just explained but with *high decrease in SCB small enterprise lending*$_{c,t}$ as the new outcome variable. *High decrease in SCB small enterprise lending*$_{c,t}$ is a

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

dummy variable equal to 1 if SCB small enterprise lending dropped by over 60% in year t and county c compared to the previous year. Table G.2 reports estimation results, with the coefficient of interest (the interaction of $treated_c$ and $post_t$) being always positive and displaying consistent magnitudes across specifications, and approaching significance under the heavier fixed effects loadings (columns 2 and 4).

Results appear very similar when picking lower thresholds in defining the variable $high\ decrease\ in\ SCB\ small\ enterprise\ lending_{c,t}$ (20%, 30%, 40%, and 50% decreases in SCBs small enterprise lending, not reported). The interaction term is always positive and hovers around significance, suggesting a greater likelihood of high small enterprise decreases for SCBs in treated counties after the event (a $\sim 50\%$ increase with respect to the unconditional sample average). Despite the wavering significance in coefficients, according to Figure G.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. Therefore, SCBs appear more likely to significantly reduce small enterprise lending after large mobile infrastructure improvements in this setting as well. The paper's main findings regarding SCB dynamics are confirmed.

7.4 Economic consequences by business size

Internet Appendix H replicates the real effects analysis of section 6.2 and table 8 across subsamples by business size. In particular, Columns 1, 4, and 7 of table H.1 report estimates for businesses with less than 20 employees. Columns 2, 5, and 8 report estimates for businesses with more than 20 employees and less than 50. Columns 3, 6, and 9 report estimates for businesses with over 50 employees. The dependent variables of interest are the standardized growth rate of the number of relevant businesses in columns 1 to 3, the standardized growth rate of employment at relevant businesses in columns 4 to 6, and the standardized earnings growth rate at relevant businesses in columns 7 to 9. Like in table 6.2, the coefficient of interest is the one on the interaction between $spectrum\ expansions_{c,t-1}$ and $share\ SCB\ deposits_{c,2010}$, separately capturing the differential effect of pre-existing SCB presence on the territory at times of heightened technological competition.

Based on previous results, we expect a negative effect for the interaction variable, decreasing in size and significance the more we transition towards larger businesses since it is the small businesses that constitute the core of the SCBs' small enterprise lending model. Across specifications, the coefficient on the interaction variable is indeed negative and significant for businesses with less than 20 employees and for businesses with between 20 and 50 employees, but not for larger businesses. Additionally, the magnitude of the interaction coefficient is smaller for businesses with between 20 and 50 employees than for businesses with less than 20 employees, confirming the expectations.[26] This further suggests that the larger the pre-existing hold of SCBs and the number of small enterprises in a county, the greater the negative economic effects of technological competition highlighted in section 6.2.

7.5 Placebo tests on spectrum expansions

Internet Appendix I contains Placebo Tests. In particular, it replicates the specifications in tables D.1, 6, and 8 while substituting the measure $sp.\ expansions_{c,t-1}$ with the same measure but randomized over time and within county ($randomized\ sp.\ exp._{c,t-1}$, the placebo measure). As explained in Internet Appendix D, spectrum expansions are ever-increasing (and moved by both nationwide policies and repurposing of local radio and TV frequencies). It is common knowledge that over the time frame of the analysis, deposits have also increased (nearly doubled), especially at larger banks. If all coefficients on $randomized\ sp.\ exp._{c,t-1}$ are insignificant whereby coefficients on $sp.\ expansions_{c,t-1}$ were previously significant, then

[26]Magnitudes being directly comparable thanks to the standardization of the dependent variables.

the analysis conducted so far is indeed picking up dynamics strictly related to times of heightened technological competition rather than concurrent growing trends in deposits and technology.

Table I.1 replicates deposit competition analysis table D.1, and all coefficients turn insignificant when using $randomized\ sp.\ exp._{c,t-1}$ instead of $sp.\ expansions_{c,t-1}$. Table I.2 replicates SCBs asset side analysis table 6, and all coefficients turn insignificant when using $randomized\ sp.\ exp._{c,t-1}$ instead of $sp.\ expansions_{c,t-1}$. Table I.3 replicates real effects analysis table 8, and all coefficients turn insignificant when using $randomized\ sp.\ exp._{c,t-1}$ instead of $sp.\ expansions_{c,t-1}$. Overall, the Placebo tests behave as expected and the analysis throughout the paper has been indeed uncovering new competition dynamics across banks linked to mobile technology adoption and popularity.

8 Conclusion

Much of the early literature on financial services digitalization has highlighted the increasing competition posed by fintech firms to the traditional banking sector. However, only recently has attention shifted to the fact that competition within the banking sector is also changing due to the varying degrees to which banks are able to digitalize their own services. This paper shows that over the 2010-2019 digitalization period, banks slow to adopt mobile technology—namely, small community banks (assets below $1 bn)—have lost significant amounts of deposits to larger, better-digitalized banks at times of heightened technological competition. Further, the introduction of the new technology has prompted a paradigm shift in the provision of small enterprise lending that has had consequences for the local economy.

Besides unveiling these unprecedented competition dynamics in an entirely reduced-form setting, the paper provides important insights into how the traditional bank business model navigates technological progress. Findings highlight how late and poor mobile technology adoption has deprived small community banks of the deposits and synergies at the core of their business model. For now, the deprivation of said synergies at small community banks is resulting in less branch-based, relationship lending, only partially replaced by the more digital lending ways of larger banks and fintech firms. Whether further technological progress will allow these ways to become a full substitute for branch-based relationship lending remains to be determined.

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Figure 1: **Mobile banking adoption and update rates over time**

Description: This figure investigates trends in mobile banking technology adoption over time. The upper panel is a plot of the percentage of FDIC-insured banks providing mobile banking services over time. The lower panel contains to the left a breakdown of the upper panel by bank type as defined in Section 3, to the right app update intensities by bank type over time. App update intensity is defined as the ratio of the total number of app updates (on both iPhone and Android) since the launch of the first app to the number of years since the launch.

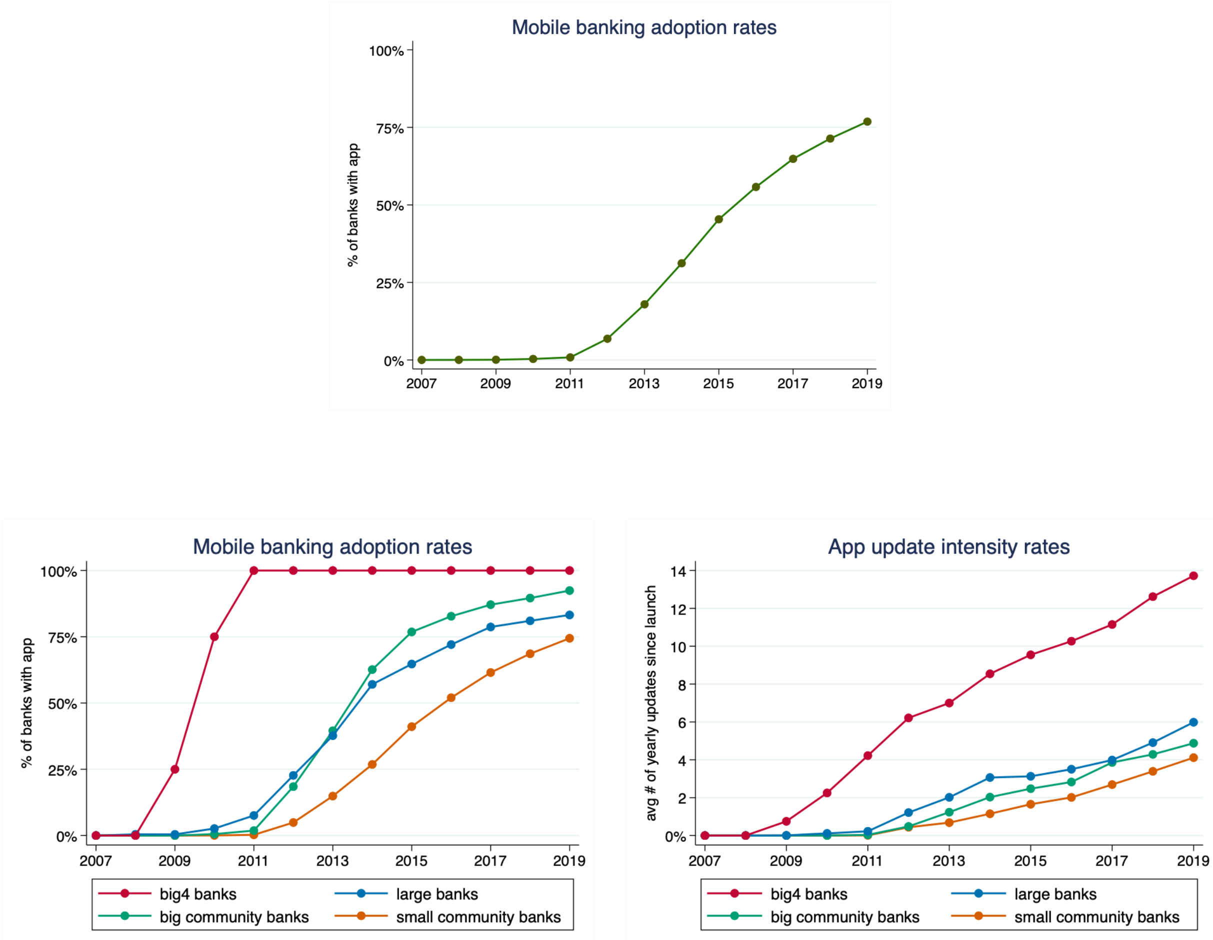


Table 1: **Summary Statistics**

Description: This table presents summary statistics for the banking sector and the mobile infrastructure data. Panel A presents two snapshots of the U.S. banking sector by bank type, in 2010 and 2019 respectively. Panel B presents summary statistics of the county-year shock introduced in subsection 4.2.1. The shock is derived by interacting the cumulative nationwide increases in electromagnetic spectrum devoted to mobile communication (in 100s of MHz, following the 2014 and 2016 Federal Communication Commission auctions) with the share of household with a mobile contract in the county the previous year (from the Census Bureau's American Community Survey). Panel C reports summary statistics for all Mobile Network Operators' spectrum expansions since 2010 across U.S. counties by year, as introduced in subsection 5/Internet Appendix D.

Panel A: The universe of FDIC-insured depository institutions

	# institutions	avg. # branches	avg. deposits	avg. # branches per county	avg. deposits per county	avg. # of counties
June 2010						
small 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	7,065	12.97	USD 976.05 mill.	2.32	USD 164.88 mill.	3.60
June 2019						
small 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	5,300	16.30	USD 2.41 bill.	2.26	USD 382.46 mill.	4.89

Panel B: County-year Shock (county-level)

year	mean	st. dev.	min	50^{th} p.	max	obs
2013	0.00	0.00	0.00	0.00	0.00	828
2014	0.24	0.06	0.09	0.24	0.42	828
2015	0.27	0.07	0.00	0.27	0.43	830
2016	0.54	0.13	0.00	0.54	0.88	831
2017	0.97	0.16	0.00	0.99	1.28	837
2018	1.04	0.13	0.00	1.05	1.32	838
2019	1.08	0.13	0.00	1.09	1.36	840
total	0.59	0.42	0.00	0.54	1.36	5,832

Panel C: Spectrum Expansions (in 100s of MHz, county-level)

year	mean	st. dev.	min	5^{th} p.	25^{th} p.	50^{th} p.	75^{th} p.	95^{th} p.	max	obs
2010	0.68	0.18	0.13	0.52	0.56	0.63	0.76	1.05	1.53	3,233
2011	0.72	0.18	0.36	0.56	0.56	0.66	0.80	1.11	1.63	3,233
2012	0.69	0.15	0.36	0.56	0.56	0.66	0.76	0.97	1.44	3,233
2013	0.78	0.22	0.38	0.56	0.58	0.74	0.88	1.17	1.85	3,233
2014	0.92	0.24	0.49	0.67	0.77	0.88	1.03	1.40	1.95	3,233
2015	1.32	0.26	0.81	0.99	1.12	1.28	1.49	1.83	2.41	3,233
2016	1.56	0.29	0.92	1.24	1.35	1.51	1.67	2.17	3.02	3,233
2017	2.35	0.36	0.40	1.85	2.13	2.31	2.56	3.03	3.63	3,233
2018	2.49	0.36	0.50	1.97	2.25	2.44	2.68	3.15	4.06	3,243
2019	2.63	0.36	0.70	2.09	2.39	2.60	2.82	3.30	4.18	3,243
total	1.41	0.80	0.13	0.56	0.69	1.16	2.17	2.83	4.18	32,360

Table 2: **App adoption**

Description: This table presents models that investigate the timing of mobile banking technology adoption. Panel A provides *hazard ratios* from a parametric survival 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 these mobile services become more and more popular. Reported 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 c branches belonging to banks that provide mobile banking apps in year t, % *deposits with* $app_{c,t}$ measures the percentage of county c deposits held at banks that provide mobile banking apps in year t. Standard errors are clustered at county level in Panel B; ***, **, * denote 1%, 5%, and 10% statistical significance.

Panel A: Hazard model

	app available $_{b,t}$
	(1)
big community bank $_{b,t-1}$	2.0577***
	(0.1047)
large bank $_{b,t-1}$	1.2953***
	(0.0984)
big 4 bank $_{b,t-1}$	34.5137***
	(10.5369)
deposit-weighted avg % of pop. 65y and older $_{b,t-1}$	0.8209***
	(0.0316)
deposit-weighted avg % of pop. w/higher education $_{b,t-1}$	1.0752**
	(0.0244)
ROA $_{b,t-1}$	1.5754
	(0.9323)
net interest margin $_{b,t-1}$	2.7205
	(5.1230)
tier 1 lev. capital ratio $_{b,t-1}$	0.9637***
	(0.0039)
observations	60,276

Panel B: Linear regression models

	% branches providing app $_{c,t}$		% deposits with app $_{c,t}$	
	(1)	(2)	(3)	(4)
% pop. 65y and older $_{c,2010}$	-0.465***	-0.108***	-0.522***	-0.139***
	(0.044)	(0.042)	(0.048)	(0.045)
% pop. w/higher education $_{c,2010}$	0.393***	0.125***	0.456***	0.168***
	(0.028)	(0.027)	(0.034)	(0.032)
I(big comm. bank branches $_{c,t}$)		0.0411***		0.0418***
		(0.0047)		(0.0051)
I(large bank branches $_{c,t}$)		0.0810***		0.0859***
		(0.0078)		(0.0082)
I(big4 bank branches $_{c,t}$)		0.107***		0.117***
		(0.0055)		(0.0061)
state FE	x	x	x	x
year FE	x	x	x	x
observations	41,098	41,098	41,098	41,098
R-squared	0.748	0.770	0.721	0.745
Within R2	0.0355	0.120	0.0394	0.122

Table 3: **Mobile Technology and Bank Deposits**

Description: This table employs a two-way fixed effects difference-in-differences setting to investigate how bank-level deposits evolve around the adoption of mobile technology. The dependent variable $ln(deposits_{b,t})$ is the natural logarithm of bank b deposits in year t. *App available*$_{b,t-1}$ is a dummy equal to 1 if bank b offers a banking app in year t-1. $I(SCB)$, $I(BCB)$, $I(LB)$, and $I(B4B)$ are dummies for bank b being either a small community bank or a big community bank or a large bank or a big 4 bank, respectively. Standard errors are clustered at bank level in Panel A; ***, **, * denote 1%, 5%, and 10% statistical significance.

	ln(deposits $_{b,t}$)		
	(1)	(2)	(3)
app available $_{b,t-1}$	0.0944***	0.0819***	
	(0.0083)	(0.0067)	
app available $_{b,t-1}$*I(SCB)			0.0308***
			(0.0068)
app available $_{b,t-1}$*I(BCB)			0.227***
			(0.017)
app available $_{b,t-1}$*I(LB)			0.459***
			(0.034)
app available $_{b,t-1}$*I(B4B)			0.383***
			(0.094)
ROA $_{b,t-1}$		4.801***	4.746***
		(1.14)	(1.13)
net interest margin $_{b,t-1}$		-1.212*	-1.167*
		(0.71)	(0.70)
tier 1 lev. capital ratio $_{b,t-1}$		-0.00257***	-0.00260***
		(0.00078)	(0.00078)
year FE	x	x	x
bank FE	x	x	x
observations	80,477	76,654	76,654
R-squared	0.957	0.965	0.966

Table 4: **Technology-driven Competition on Deposits**

Description: This table presents results on technology-driven competition on deposits. Across panels, the dependent variable is the natural logarithm of bank b deposits in county c and year t. Across specifications, *county-year shock*$_{c,t-1}$ captures faster implementation of country-wide mobile infrastructure improvements policies and *app available*$_{b,t-1}$ is a dummy equal to 1 if bank b offers a banking app in year t-1. Across panels, *app available (early/late adopter in county)*$_{b,c,t-1}$ is a bank that has introduced mobile banking services before/after the median mobile banking services introduction year of the banks operating in the county, and *App update intensity* is defined as the ratio of the total number of app updates (on both iPhone and Android) since the launch of the first app to the number of years since the launch. In panel B, $I(SCB)$, $I(BCB)$, $I(LB)$, and $I(B4B)$ are dummies for bank b being either a small community bank or a big community bank or a large bank or a big 4 bank, respectively. Standard errors are clustered at county level; ***, **, *, + denote 1%, 5%, 10% and 15% statistical significance; - denotes a coefficient absorbed by fixed effects.

Panel A: Deposit Flows and App Availability

	ln(deposits $_{b,c,t}$)			
	(1)	(2)	(3)	(4)
county-year shock $_{c,t-1}$	-0.0852*	-0.0712+	-	-0.123**
	(0.047)	(0.047)		(0.053)
app available $_{b,t-1}$	-0.0745***		-0.0720***	-0.0431*
	(0.013)		(0.014)	(0.023)
app available $_{b,t-1}$ × county-year shock $_{c,t-1}$	0.123***		0.117***	0.0406
	(0.027)		(0.028)	(0.033)
app available (early adopter in county) $_{b,c,t-1}$		-0.0161		
		(0.049)		
app available (early adopter in county) $_{b,c,t-1}$ × county-year shock $_{c,t-1}$		0.175***		
		(0.029)		
app available (late adopter in county) $_{b,c,t-1}$		-0.0219+		
		(0.015)		
app available (late adopter in county) $_{b,c,t-1}$ × county-year shock $_{c,t-1}$		0.0489*		
		(0.029)		
app updates intensity $_{b,t-1}$				0.000198
				(0.0024)
county-year shock $_{c,t-1}$ × app updates intensity $_{b,t-1}$				0.00849***
				(0.0024)
county-year controls:				
ln(population $_{c,t-1}$)	0.289	0.332	-	0.500
	(0.26)	(0.26)		(0.36)
ln(# businesses above 100 employees $_{c,t-1}$)	0.00384	-0.00335	-	0.0181
	(0.043)	(0.044)		(0.051)
ln(# businesses below 100 employees $_{c,t-1}$)	-0.0921	-0.109	-	-0.292
	(0.18)	(0.18)		(0.27)
employment rate $_{c,t-1}$	-0.739	-0.657	-	0.00674
	(0.54)	(0.54)		(0.65)
ln(personal income pc $_{c,t-1}$)	0.117	0.111	-	0.101
	(0.11)	(0.11)		(0.16)
ln(county GDP $_{c,t-1}$)	0.195**	0.191**	-	0.212**
	(0.085)	(0.086)		(0.097)
bank-year controls:				
# branches $_{b,c,t-1}$	0.0751***	0.0752***	0.0750***	0.0681***
	(0.014)	(0.014)	(0.014)	(0.014)
ROA $_{b,t-1}$	0.530	0.555	0.793	1.809
	(0.91)	(0.91)	(0.92)	(2.10)
net interest margin $_{b,t-1}$	1.531	1.504	1.478	0.488
	(1.57)	(1.57)	(1.56)	(2.66)
tier 1 lev. capital ratio $_{b,t-1}$	-0.00784	-0.00747	-0.00578	0.00114
	(0.0058)	(0.0058)	(0.0057)	(0.0047)
bank FE	x	x	x	x
county FE	x	x		x
year FE	x	x		x
county x year FE			x	
observations	101,323	101,323	101,323	61,239
R-squared	0.644	0.644	0.648	0.665

Panel B: Deposit Flows and App Availability by Bank Type

	ln(deposits $_{b,c,t}$)			
	(1)	(2)	(3)	(4)
county-year shock $_{c,t-1}$	-0.0683^{+}	-0.141**	-	-0.0633
	(0.047)	(0.064)		(0.047)
app available $_{b,t-1}$*I(SCB)	-0.0158	0.0165	-0.00621	
	(0.018)	(0.021)	(0.020)	
app available $_{b,t-1}$*I(SCB) × county-year shock $_{c,t-1}$	0.00453	-0.00642	-0.00936	
	(0.032)	(0.038)	(0.034)	
app available $_{b,t-1}$*I(BCB)	0.0257	0.0151	0.0347	
	(0.030)	(0.035)	(0.031)	
app available $_{b,t-1}$*I(BCB) × county-year shock $_{c,t-1}$	0.0876**	0.0126	0.0664*	
	(0.037)	(0.073)	(0.039)	
app available $_{b,t-1}$*I(LB)	-0.0699***	-0.0670***	-0.0691***	
	(0.021)	(0.023)	(0.022)	
app available $_{b,t-1}$*I(LB) × county-year shock $_{c,t-1}$	0.130***	0.114**	0.133***	
	(0.031)	(0.046)	(0.033)	
app available $_{b,t-1}$*I(B4B)	-	-	-	-
app available $_{b,t-1}$*I(B4B) × county-year shock $_{c,t-1}$	0.257***	1.106***	0.258***	
	(0.038)	(0.36)	(0.040)	
app available (early adopter in county) $_{b,t-1}$*I(SCB)				-0.0550
				(0.100)
app available (early adopter in county) $_{b,t-1}$*I(SCB) × county-year shock $_{c,t-1}$				0.00577
				(0.065)
app available (late adopter in county) $_{b,t-1}$*I(SCB)				-0.000124
				(0.024)
app available (late adopter in county) $_{b,t-1}$*I(SCB) × county-year shock $_{c,t-1}$				-0.00684
				(0.034)
app available (early adopter in county) $_{b,t-1}$*I(BCB)				0.0720
				(0.094)
app available (early adopter in county) $_{b,t-1}$*I(BCB) × county-year shock $_{c,t-1}$				0.163***
				(0.056)
app available (late adopter in county) $_{b,t-1}$*I(BCB)				0.0445
				(0.039)
app available (late adopter in county) $_{b,t-1}$*I(BCB) × county-year shock $_{c,t-1}$				0.0435
				(0.043)
app available (early adopter in county) $_{b,t-1}$*I(LB)				0.00560
				(0.060)
app available (early adopter in county) $_{b,t-1}$*I(LB) × county-year shock $_{c,t-1}$				0.158***
				(0.035)
app available (late adopter in county) $_{b,t-1}$*I(LB)				-0.0451**
				(0.023)
app available (late adopter in county) $_{b,t-1}$*I(LB) × county-year shock $_{c,t-1}$				0.0858**
				(0.036)
app available (early adopter in county) $_{b,t-1}$*I(B4B)				0.0257
				(0.18)
app available (early adopter in county) $_{b,t-1}$*I(B4B) × county-year shock $_{c,t-1}$				0.258***
				(0.038)
app available (late adopter in county) $_{b,t-1}$*I(B4B)				-
app available (late adopter in county) $_{b,t-1}$*I(B4B) × county-year shock $_{c,t-1}$				0.0668
				(0.11)
county-year controls	x	x	x	x
bank-year controls	x	x	x	x
bank FE	x	x	x	x
bank type x year FE		x		
county FE	x	x		x
year FE	x			x
county x year FE			x	
observations	101,323	101,323	101,323	101,323
R-squared	0.644	0.645	0.648	0.645

Table 5: **Technology-driven Competition and Branch Dynamics**

Description: This table presents results on technology-driven competition on branch dynamics. The dependent variable is a dummy equal to one if in county c, year t there are less *bank type* branches in year t than in year $t-1$. Across specifications, *county-year shock*$_{c,t-1}$ captures faster implementation of country-wide mobile infrastructure improvements policies and $\%\, of\ bank\ type\ branches\ with\ app_{\ bank\ type,c,t-1}$ is the percentage of *bank type* branches that provide mobile banking services 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.

	at least one net closing $_{b,c,t}$			
	incl. acquisitions			excl. acquisitions
	(1)	(2)	(3)	(4)
% of bank type branches with app $_{bank\ type,c,t-1}$			-0.0472***	
			(0.014)	
county-year shock $_{c,t-1}$*I(SCB)	0.0773^{+}	0.270***	0.153**	0.119*
	(0.048)	(0.075)	(0.062)	(0.068)
county-year shock $_{c,t-1}$*I(SCB) × % of bank type branches with app $_{SCB,c,t-1}$			-0.117**	
			(0.051)	
county-year shock $_{c,t-1}$*I(BCB)	-0.0817*	0.0290	-0.230***	-0.00486
	(0.047)	(0.076)	(0.068)	(0.065)
county-year shock $_{c,t-1}$*I(BCB) × % of bank type branches with app $_{BCB,c,t-1}$			0.163***	
			(0.054)	
county-year shock $_{c,t-1}$*I(LB)	0.180***	-0.0367	0.103	0.0430
	(0.048)	(0.077)	(0.077)	(0.072)
county-year shock $_{c,t-1}$*I(LB) × % of bank type branches with app $_{LB,c,t-1}$			0.0798	
			(0.071)	
county-year shock $_{c,t-1}$*I(B4B)	0.0325	-0.0517	0.0327	0.0348
	(0.048)	(0.074)	(0.049)	(0.071)
county-year shock $_{c,t-1}$*I(B4B) × % of bank type branches with app $_{B4B,c,t-1}$			-	
county-year controls	x	x	x	x
county FE	x	x	x	x
year FE	x		x	
bank type x year FE		x		x
observations	19,501	19,501	19,401	19,501
R-squared	0.118	0.135	0.119	0.127

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

Description: This table investigates the impact of the mobile technology shock on the asset side of small community banks' balance sheet. In columns 1-3 of Panel A the dependent variable is the sum of commercial and industrial loans below \$1mn and of farm loans below \$0.5mn over assets for small community bank b having the majority of its deposits in county c and year t, in columns 4-6 is real estate loans over assets, in columns 7-9 individual loans over assets. For each lending type, the first column has *county-year shock*$_{c,t-1}$ as the main independent variable of interest over its full sample (2013-2019, counties with more than 65,000 residents), the second one has *sp. expansions*$_{c,t-1}$ as the main independent variable of interest over the subsample in which the previous *county-year shock*$_{c,t-1}$ measure is available, the third one has *sp. expansions*$_{c,t-1}$ as the main independent variable of interest over its full sample (2010-2019, all counties). For Panel B, the dependent variable is the natural logarithm of the sum of commercial and industrial loans below \$1mn and of farm loans below \$0.5mn on the balance sheet of small community bank b having the majority of its deposits in county c and year t. Across panels, *county-year shock*$_{c,t-1}$ captures faster implementation of nationwide mobile infrastructure capacity improvements policies, and *sp. expansions*$_{c,t-1}$ capture actual mobile spectrum expansions since 2010 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 to correct for potential measurement errors in linking each small community bank to the county it has most of its deposits in (still robust to clustering at county level); ***, **, *, $^{+}$ denote 1%, 5%, 10% and 15% statistical significance; - denotes a coefficient absorbed by fixed effects.

Panel A: Lending

	small enterprise loans over assets $_{b,t}$			real estate loans o/assets $_{b,t}$			individual loans o/assets $_{b,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	full sample	cy-shock subsample	full sample	full sample	cy-shock subsample	full sample	full sample	cy-shock subsample	full sample
county-year shock $_{c,t-1}$	-0.00353			-0.0123**			0.00327**		
	(0.0038)			(0.0054)			(0.0015)		
sp. expansions $_{c,t-1}$		-0.00905***	-0.00412***		0.0176***	0.00230^{+}		0.00125	0.00330***
		(0.0015)	(0.0010)		(0.0031)	(0.0014)		(0.0013)	(0.00064)
county-year controls	x	x	x	x	x	x	x	x	x
bank-year controls	x	x	x	x	x	x	x	x	x
bank FE	x	x	x	x	x	x	x	x	x
county FE	x	x	x	x	x	x	x	x	x
year FE	x	x	x	x	x	x	x	x	x
observations	15,148	15,148	49,236	15,148	15,148	49,236	15,148	15,148	49,236
R-squared	0.899	0.899	0.861	0.927	0.927	0.920	0.940	0.940	0.903

Panel B: Small Business Lending, Digitalization Channel

	ln(amount small enterprise loans $_{b,t}$)				
	(1)	(2)	(3)	(4)	(5)
	full sample	full sample	full sample	full sample	above med. LB deposits
county-year shock $_{c,t-1}$	-0.126		-0.191^{+}		
	(0.13)		(0.13)		
sp. expansions $_{c,t-1}$		-0.108**		-0.110**	-0.0992**
		(0.043)		(0.044)	(0.043)
app available $_{b,t-1}$			0.0409*	0.0127	-0.0208
			(0.021)	(0.034)	(0.039)
app available $_{b,t-1}$ × county-year shock $_{c,t-1}$			0.114***		
			(0.038)		
app available $_{b,t-1}$ × sp. expansions $_{c,t-1}$				0.00851	0.0517**
				(0.017)	(0.026)
county-year controls	x	x	x	x	x
bank-year controls	x	x	x	x	x
county FE	x	x	x	x	x
year FE	x	x	x	x	x
bank FE	x	x	x	x	x
observations	15,148	49,236	15,148	49,236	23,908
R-squared	0.931	0.827	0.931	0.827	0.894

Table 7: **Small Business Lending by Other Actors**

Description: This table investigates concurrent small business lending patterns at CRA filers (big community banks, large banks, big 4 banks) in Panel A and fintech firms in Panel B. In columns 1 and 2 of Panel A, the dependent variable is the natural logarithm of the amount of CRA loans originated by bank b in year t and county c, where it operates branches. In columns 3 to 6, the dependent variable is the natural logarithm of the amount of CRA loans originated by bank b in year t and county c, where it does not operates branches. In Panel B, the dependent variable is he first difference in the number of secured small business loans granted by fintech firms in county c and year t (data are from UCC Filings courtesy of Gopal and Schnabl (2022)). Across panels, $\textit{county-year shock}_{c,t-1}$ captures faster implementation of nationwide mobile infrastructure improvements policies, and $\textit{sp. expansions}_{c,t-1}$ capture actual mobile spectrum expansions since 2010 in county c and year t-1. In Panel A, columns 1 and 4 have $\textit{county-year shock}_{c,t-1}$ as the main independent variable of interest over its full sample (2013-2019, counties with more than 65,000 residents), columns 2 and 5 have $\textit{sp. expansions}_{c,t-1}$ as the main independent variable of interest over the subsample in which the previous $\textit{county-year shock}_{c,t-1}$ measure is available, columns 3-6-7-8 have $\textit{sp. expansions}_{c,t-1}$ as the main independent variable of interest over its full sample. In Panel B, column 1 covers the full sample, column 2 and 3 split the sample in counties with more and less than 65,000 residents, respectively. Standard errors are clustered at county level; ***, **, *,$^{+}$ denote 1%, 5%, 10%, and 15% statistical significance; - denotes a coefficient absorbed by fixed effects.

Panel A: Small Enterprise Lending by Larger Banks

	ln(amount ⌊ ⌉ CRA Small Enterprise Lending $_{b,c,t}$)							
	⌊ ⌉ = branch-based			⌊ ⌉ = remote/digital				
	(1) full sample	(2) cy-shock subsample	(3) full sample	(4) full sample	(5) cy-shock subsample	(6) full sample	(7) full sample	(8) full sample
county-year shock $_{c,t-1}$	-0.0428			-0.0539				
	(0.058)			(0.042)				
sp. expansions $_{t-1}$		-0.0433	-0.0192		0.0353*	0.0500***	0.00889	-
		(0.027)	(0.021)		(0.021)	(0.012)	(0.014)	
app available $_{b,t-1}$							-0.141***	-0.157***
							(0.010)	(0.010)
app available $_{b,t-1}$ × sp. expansions $_{t-1}$							0.0606***	0.0698***
							(0.0068)	(0.0069)
county-year controls	x	x	x	x	x	x	x	x
bank-year controls	x	x	x	x	x	x	x	x
bank FE	x	x	x	x	x	x	x	x
bank type x year FE	x	x	x	x	x	x	x	x
county FE	x	x	x	x	x	x	x	
county x year FE								x
observations	51,267	51,267	107,501	231,324	231,324	670,640	670,640	670,635
R-squared	0.727	0.727	0.701	0.437	0.437	0.425	0.425	0.440

Panel B: Small Enterprise Lending by Fintech

	# FT SBLs $_{c,t}$ - # FT SBLs $_{c,t-1}$		
	(1) full sample	(2) pop.>65,000	(3) pop.<65,000
sp. expansion $_{c,t-1}$	2.740***	5.313**	0.0175
	(0.68)	(2.46)	(0.086)
county-year controls	x	x	x
county FE	x	x	x
year FE	x	x	x
observations	20,944	5,454	15,490
R-squared	0.642	0.650	0.106

Table 8: **Real Effects**

Description: This table presents results on the real effects of the mobile technology shock accounting for small community bank dynamics. The dependent variables are county GDP growth in columns 1-2-3, growth in the number of county small businesses in column 4, county small business employments growth in column 5, county small business wage growth in column 6. Small businesses are defined as businesses with less than 50 employees. In column 1, *county-year shock*$_{c,t-1}$ captures faster implementation of country-wide mobile infrastructure improvements policies. In columns 2 to 6, *sp. expansions*$_{c,t-1}$ capture actual mobile spectrum expansions since 2010 in county c and year t-1. Across columns, $SCB\ deposits\%_{c,2010}$ is small community banks' deposits over total deposits in county c in 2010. Column 1 has *county-year shock*$_{c,t-1}$ as the main independent variable of interest over its full sample (2013-2019, counties > 65,000 residents), column 2 has *sp. expansions*$_{c,t-1}$ as the main independent variable of interest over the subsample in which the previous *county-year shock*$_{c,t-1}$ measure is available, columns 3-4-5-6 have *sp. expansions*$_{c,t-1}$ as the main independent variable of interest over its full sample (2010-2019, all counties). Standard errors are clustered at county level; ***, **, *, + denote 1%, 5%,, 10% and 15% statistical significance; - denotes a coefficient absorbed by fixed effects.

	County GDP growth $_{c,t}$			Small Business gr. $_{c,t}$	SB employment gr. $_{c,t}$	SB wage gr. $_{c,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
	full sample	cy-shock subsample	full sample	full sample	full sample	full sample
county-year shock $_{c,t-1}$	0.0173*					
	(0.0097)					
SCB deposits % $_{c,2010}$	-	-	-	-	-	-
SCB deposits % $_{c,2010}$ × county-year shock $_{c,t-1}$	-0.0162**					
	(0.0065)					
sp. exp. $_{c,t-1}$		0.00359	0.0391***	0.00269**	-0.000799	0.00609***
		(0.0033)	(0.0046)	(0.0013)	(0.0017)	(0.0018)
SCB deposits % $_{c,2010}$ × sp. exp. $_{c,t-1}$		-0.00989***	-0.0356***	-0.00417***	-0.00526***	-0.00552***
		(0.0037)	(0.0040)	(0.0011)	(0.0017)	(0.0015)
county-year controls	x	x	x	x	x	x
county FE	x	x	x	x	x	x
year FE	x	x	x	x	x	x
observations	5,519	5,519	28,084	28,084	27,150	27,514
R-squared	0.299	0.299	0.221	0.151	0.196	0.0887

Internet Appendix to:

Keeping up in digital era: a traditional bank perspective.

(intended for online publication)

Appendix A - Variable Descriptions

Main analysis, in order of appearance:

Name	Explanation
ln(deposits$_{b,c,t}$)	Natural logarithm of bank b deposits in county c and year t. *Source: FDIC Summary of Deposits.*
sp. expansions$_{c,t-1}$	Additional spectrum allotted to Mobile Network Operators in county c and year t-1 since 2010 (hundreds of MHz). *Source: Federal Communication Commission Licenses.*
placebo sp. expansions$_{c,t-1}$	Randomization of *sp. expansions*$_{c,t-1}$ over time within county.
app available$_{b,t-1}$	Dummy variable = 1 if bank b provides mobile banking services in year t-1. *Source: hand-collected data from data.ai.*
ln(population$_{c,t-1}$)	Natural logarithm of county c population in year t-1. *Source: Census Bureau.*
ln(# businesses$_{c,t-1}$)	Natural logarithm of county c number of businesses in year t-1. *Source: Census County Business Patterns.*
employment rate$_{c,t-1}$	Employment rate [0,1] of county c in year t-1. *Source: Bureau of Labor Statistics.*
ln(personal income pc$_{c,t-1}$)	Natural logarithm of personal income per capita in county c and year t-1. *Source: Bureau of Economic Analysis.*
ln(county GDP$_{c,t-1}$)	Natural logarithm of county c GDP in year t-1. *Source: Bureau of Economic Analysis.*
# branches$_{b,c,t-1}$	Number of branches of bank b in county c and year t-1. *Source: FDIC Summary of Deposits.*
NPLs over assets$_{b,t-1}$	Ratio of nonperforming loans to assets of bank b in year t-1. *Source: Call Reports.*
net income over assets$_{b,t-1}$	Ratio of net income to assets of bank b in year t-1. *Source: Call Reports.*
legacy in county$_{b,c,t-1}$	Dummy variable = 1 if bank b runs a branch in county c and year t-1 that has been serving the county for more than 43 years (median sample branch age). *Source: FDIC Summary of Deposits.*
# counties covered$_{b,t-1}$	Number of counties where bank b has branches in year t-1. *Source: FDIC Summary of Deposits.*
deposit spread %$_{b,c,t}$	Fed funds rate minus bank b's county c average of Money-Market 25-year rates at rate-setting branches. Quarterly frequency. *Source: RateWatch.*
big community bank$_{b,t}$	Dummy variable = 1 if bank b is a *big community bank* in year t. *Source: bank type framework (Section 3).*
large bank$_{b,t}$	Dummy variable = 1 if if bank b is a *large bank* in year t. *Source: bank type framework (Section 3).*
big4 bank$_{b,t}$	Dummy variable = 1 if if bank b is a *big4 bank* in year t. *Source: bank type framework (Section 3).*

Name	Description
non-community bank$_{b,t}$	Dummy variable = 1 if bank b is either a *large bank* or a *big4 bank* in year t. *Source: bank type framework (Section 3).*
deposit-weighted avg sp. expansions$_{b,t-1}$	Deposit-weighted average of *sp. expansions*$_{c,t-1}$ across the counties bank b operates in. *Source: based on FCC Licenses & FDIC Summary of Deposits.*
deposit-weighted % pop. 65y and older$_{b,t-1}$	Deposit-weighted average of the percentage [0,1] of population 65-year and older across the counties bank b operates in in year t-1. *Source: based on Census 2010 & FDIC Summary of Deposits.*
dep.-w. avg % of pop. w/higher ed.$_{b,t-1}$	Deposit-weighted average of the percentage [0,1] of population with higher education across the counties bank b operates in in year t-1. *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$_{c,t}$)	Dummy = 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 3).*
I(large bank branches$_{c,t}$)	Dummy = 1 if there is at least one branch belonging to a *large bank* in county c and year t. *Source: FDIC Summary of Deposits & bank type framework (Section 3).*
I(big4 bank branches$_{c,t}$)	Dummy = 1 if there is at least one branch belonging to a *big4 bank* in county c and year t. *Source: FDIC Summary of Deposits & bank type framework (Section 3).*
% of county deposits held at SCBs$_{c,t}$	Percentage [0,1] of county c deposits held at Small Community Banks in year t. *Source: FDIC Summary of Deposits & bank type framework (Section 3).*
at least one net closing$_{bank\ type,c,t}$	Dummy variable = 1 if the number of *bank type* (big comm. bank, large bank, big4 bank) branches in county c and year t is smaller than the previous year. *Source: FDIC Summary of Deposits & bank type framework (Section 3).*
at least one net opening$_{bank\ type,c,t}$	Dummy variable = 1 if the number of *bank type* (big comm. bank, large bank, big4 bank) branches in county c and year t is larger than the previous year. *Source: FDIC Summary of Deposits & bank type framework (Section 3).*
% of bank type branches with app$_{bank\ type,c,t}$	Percentage [0,1] of county c *bank type* (big comm. bank, large bank, big4 bank) branches that provide mobile banking at time t. *Source: bank type framework (Section 3) and hand-collected data from data.ai.*
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 being a small community bank and having the majority of its deposits in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits & bank type framework (Section 3).*

Name	Description
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 being a small community bank and having the majority of its deposits in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits & bank type framework (Section 3).*
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 being a small community bank and having the majority of its deposits in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits & bank type framework (Section 3).*
ln(other loans$_{b,c,t}$)	Natural logarithm of the total amount of individual loans (loans to other institutions, etc.) on the balance sheet of bank b in year t - bank b being a small community bank and having the majority of its deposits in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits & bank type framework (Section 3).*
ln(# small businesses$_{c,t-1}$)	Natural logarithm of county c number of businesses with less than 50 employees in year t-1. *Source: Census County Business Patterns.*
ln(amount total CRA SBLs$_{b,c,t}$)	Natural logarithm of the total amount of small business loans originated in county c and year t by bank b that files reports under the Community Reinvestment Act. *Source: CRA.*
ln(amount branch-based CRA SBLs$_{b,c,t}$)	Natural logarithm of the amount of small business loans originated in county c and year t by bank b that operates branches in county c and files reports under the Community Reinvestment Act. *Source: CRA & FDIC Summary of Deposits.*
ln(amount digital CRA SBLs$_{b,c,t}$)	Natural logarithm of the amount of small business loans originated in county c and year t by bank b that does not operate branches in county c and files reports under the Community Reinvestment Act. *Source: CRA & FDIC Summary of Deposits.*
I(no branch in county)$_{b,c,t}$	Dummy variable = 1 if bank b does not operate a branch in county c and year t. *Source: 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 (2022).*
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 (2022).*
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.*

Internet Appendix, in order of appearance:

Name	Description
app updates intensity$_{b,t-1}$	Ratio in year t-1 of the total number of updates that have been rolled out since launch for the outstanding App Store and Google Play apps of bank b to years since the launch. *Source: hand-collected data from data.ai.*
% BCB branches$_{c,t}$	Percentage [0,1] of county c branches belonging to big community banks in year t. *Source: FDIC Summary of Deposits & bank type framework (Section 3).*
% LB branches$_{c,t}$	Percentage [0,1] of county c branches belonging to large banks in year t. *Source: FDIC Summary of Deposits & bank type framework (Section 3).*
% Big4 branches$_{c,t}$	Percentage [0,1] of county c branches belonging to big4 banks in year t. *Source: FDIC Summary of Deposits & bank type framework (Section 3).*
% BCB deposits$_{c,t}$	Percentage [0,1] of county c deposits belonging to big community banks in year t. *Source: FDIC Summary of Deposits & bank type framework (Section 3).*
% LB deposits$_{c,t}$	Percentage [0,1] of county c deposits belonging to large banks in year t. *Source: FDIC Summary of Deposits & bank type framework (Section 3).*
% Big4 deposits$_{c,t}$	Percentage [0,1] of county c deposits belonging to big4 banks in year t. *Source: FDIC Summary of Deposits & bank type framework (Section 3).*
change in share of digital deposits$_{c,t\ vs\ t-1}$	Change in the percentage [0,1] of county c deposits held at branches that provide mobile banking services from year t-1 to year t. *Source: FDIC Summary of Deposits & bank type framework (Section 3).*
change in share of digital large bank deposits$_{c,t\ vs\ t-1}$	Change in the percentage [0,1] of county c large and big4 bank deposits held at branches that provide mobile banking services from year t-1 to year t. *Source: FDIC Summary of Deposits & bank type framework (Section 3).*
ln(# businesses $<$ 100 headcount$_{c,t}$)	Natural logarithm of county c number of businesses with less than 100 employees in year t. *Source: Quarterly Workforce Indicators.*
ln(# businesses $>$ 100 headcount$_{c,t}$)	Natural logarithm of county c number of businesses with more than 100 employees in year t. *Source: Quarterly Workforce Indicators.*
ln(# C&I loans $<$ 1 mill.$_{c,t}$)	Natural logarithm of the number of commercial and industrial loans below $1 million on the balance sheet of small community banks in year t - small community banks having the majority of their deposits in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits & bank type framework (Section 3).*
ln(am. C&I loans $<$ 1 mill.$_{c,t}$)	Natural logarithm of the amount of commercial and industrial loans below $1 million on the balance sheet of small community banks in year t - small community banks having the majority of its deposits in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits & bank type framework (Section 3).*

Appendix B - Technology-driven Competition and Deposit Pricing

This appendix explores local patterns in deposit pricing around a positive shock to the usability and popularity of mobile services (an increase in *county-year* $shock_{c,t-1}$, as explained in section 4.2.1). Specifications mirror the ones in table 4 on deposit flows and are based on equation 3. The outcome variable is the spread on deposits, calculated as the difference between the Fed Funds Rate and the (county-bank average of the) rate charged on certificates of deposit (panel A of table B.1) or on money market accounts (panel B of table B.1). Data are from RateWatch, and I only consider rate-setting branches in the analysis since I am interested in active competition on deposit pricing.[27] Due to both the incomplete coverage of RateWatch data and the further restriction to rate-setting branches, the sample coverage is limited compared to the parallel analysis on deposit flows in Table 4. Furthermore, the frequency is quarterly here instead of annually.

Columns 1 and 2 across both Panels of Table B.1 suggest that a positive shock to the usability and popularity of mobile services leads to lower spreads in the county (negative and significant coefficient on *county-year* $shock_{c,t-1}$, synonym of increased competition on deposit pricing). However, banks that provide mobile banking services do not have to lower their deposit spreads as much when compared to banks without apps (positive and significant coefficient on the interaction of *county-year* $shock_{c,t-1}$ with *app* $available_{b,t-1}$, albeit lower in magnitude than the coefficient on the county-year shock alone). This suggests that banks with mobile banking services lever their technological advantage and do not need to raise their rates as much as banks that do not provide such services at times of heightened competition. App availability per se seems to lower spreads instead, but columns 3 and 4 show that this dynamic is driven by large banks only—likely the large banks that also adopt late, already

[27] In a similar fashion to Drechsler et al. (2017).

on a downward trend, as highlighted in section 4. Column 3 and 4 further show how it is only bank types that tend to produce apps of higher quality (LBs and B4Bs) that do not need to raise their rates as much (positive and significant coefficients on the interaction of the county-year shock with app availability for them), whereas bank types with lower app quality try to lure new customer in with higher rates instead.

Overall, this appendix highlights how the existence of technology-spurred competition across banks is also reflected in deposit pricing dynamics. In particular, high-quality mobile technology enables banks to maintain their deposit spreads high (and rates low), whereas less-digitalized banks have to compensate with lower deposit spreads (and higher rates).

Table B.1: **Technology-driven Competition and Deposit Pricing**

Description: This table explores local patterns in deposit pricing around a positive shock to the usability and popularity of mobile services (an increase in *county-year shock*$_{c,t-1}$, as explained in section 4.2.1). Specifications mirror the ones for table 4 and are based off of equation 3. In Panel A, the outcome variable is the spread on deposits calculated as the difference between the Fed Funds Rate and the (county-bank average of the) rate on 12-month certificates of deposit with an account size of $10K. In Panel B, the outcome variable is the spread on deposits calculated as the difference between the Fed Funds Rate and the (county-bank average of the) rate on money market deposit accounts with an account size of $25K. Across panels, columns 1-2 focus on app availability alone, columns 3-4 distinguish the bank type of the bank providing the app. Specifications mirror the ones in table 4, albeit under quarterly frequency. Standard errors are clustered at county level; ***, **, * denote 1%, 5%, and 10% statistical significance; - denotes a coefficient absorbed by fixed effects.

Panel A: Deposit Pricing - Deposit Certificates

	deposit spread $_{b,c,t}$			
	(1)	(2)	(3)	(4)
county-year shock $_{c,t-1}$	-0.193***	-	-0.137**	-
	(0.058)		(0.057)	
app available $_{b,t-1}$	-0.116***	-0.124***		
	(0.0095)	(0.010)		
app available $_{b,t-1}$ × county-year shock $_{c,t-1}$	0.0792***	0.0810***		
	(0.020)	(0.022)		
app available $_{b,t-1}$*I(SCB)			0.0110**	0.00738
			(0.0047)	(0.0053)
app available $_{b,t-1}$*I(SCB) × county-year shock $_{c,t-1}$			-0.135***	-0.130***
			(0.024)	(0.025)
app available $_{b,t-1}$*I(BCB)			0.0193	0.0370*
			(0.018)	(0.020)
app available $_{b,t-1}$*I(BCB) × county-year shock $_{c,t-1}$			-0.112***	-0.132***
			(0.035)	(0.037)
app available $_{b,t-1}$*I(LB)			-0.221***	-0.220***
			(0.018)	(0.019)
app available $_{b,t-1}$*I(LB) × county-year shock $_{c,t-1}$			0.248***	0.248***
			(0.022)	(0.026)
app available $_{b,t-1}$*I(B4B)			-	-
app available $_{b,t-1}$*I(B4B) × county-year shock $_{c,t-1}$			0.222***	0.277***
			(0.027)	(0.035)
county-year controls	x	x	x	x
bank-year controls	x	x	x	x
bank FE	x	x	x	x
county FE	x		x	
quarter FE	x		x	
county x quarter FE		x		x
observations	89,042	85,206	89,042	85,206
R-squared	0.914	0.934	0.918	0.938

Panel B: Deposit Pricing - Money Market Accounts

	deposit spread $_{b,c,t}$			
	(1)	(2)	(3)	(4)
county-year shock $_{c,t-1}$	-0.0555**	-	-0.0456*	-
	(0.027)		(0.027)	
app available $_{b,t-1}$	-0.0243***	-0.0271***		
	(0.0040)	(0.0047)		
app available $_{b,t-1}$ × county-year shock $_{c,t-1}$	0.0286**	0.0344***		
	(0.011)	(0.013)		
app available $_{b,t-1}$*I(SCB)			0.0110**	0.00738
			(0.0047)	(0.0053)
app available $_{b,t-1}$*I(SCB) × county-year shock $_{c,t-1}$			-0.0200	-0.0139
			(0.012)	(0.013)
app available $_{b,t-1}$*I(BCB)			0.00217	0.00843
			(0.0064)	(0.0067)
app available $_{b,t-1}$*I(BCB) × county-year shock $_{c,t-1}$			0.00264	-0.00415
			(0.014)	(0.015)
app available $_{b,t-1}$*I(LB)			-0.0463***	-0.0468***
			(0.0076)	(0.0084)
app available $_{b,t-1}$*I(LB) × county-year shock $_{c,t-1}$			0.0581***	0.0673***
			(0.013)	(0.015)
app available $_{b,t-1}$*I(B4B)			-	-
app available $_{b,t-1}$*I(B4B) × county-year shock $_{c,t-1}$			0.0950***	0.112***
			(0.011)	(0.013)
county-year controls	x	x	x	x
bank-year controls	x	x	x	x
bank FE	x	x	x	x
county FE	x		x	
quarter FE	x		x	
county x quarter FE		x		x
observations	85,462	81,407	85,462	81,407
R-squared	0.983	0.986	0.983	0.986

Appendix C - Branch openings

Table C.1: **Technology-driven Competition and Branch Dynamics**

Description: This table presents results on technology-driven competition on branch dynamics. The dependent variable is a dummy equal to one if in county c, year t there are more *bank type* branches in year t than in year $t-1$. Across specifications, *county-year shock*$_{c,t-1}$ captures faster implementation of country-wide mobile infrastructure improvements policies and $\% of\, bank\, type\, branches\, with\, app_{bank\ type,c,t-1}$ is the percentage of *bank type* branches that provide mobile banking services in county c and year $t-1$. Standard errors are clustered at county level; ***, **, * denote 1%, 5%, and 10% statistical significance; - denotes a coefficient absorbed by fixed effects.

	at least one net opening $_{bank\,type,c,t}$		
	(1)	(2)	(3)
% of bank type branches with app $_{bank\,type,c,t}$			-0.0699***
			(0.011)
county-year shock $_{c,t-1}$*I(SCB)	-0.0368	-0.169***	-0.205***
	(0.037)	(0.055)	(0.043)
county-year shock $_{c,t-1}$*I(SCB) × % of bank type branches with app $_{SCB,c,t}$			0.218***
			(0.033)
county-year shock $_{c,t-1}$*I(BCB)	0.110***	0.0913	-0.0197
	(0.037)	(0.069)	(0.057)
county-year shock $_{c,t-1}$*I(BCB) × % of bank type branches with app $_{BCB,c,t}$			0.140***
			(0.051)
county-year shock $_{c,t-1}$*I(LB)	0.0429	0.0937	0.0839
	(0.037)	(0.061)	(0.060)
county-year shock $_{c,t-1}$*I(LB) × % of bank type branches with app $_{LB,c,t}$			-0.0381
			(0.057)
county-year shock $_{c,t-1}$*I(B4B)	-0.170***	-0.0692**	-0.148***
	(0.036)	(0.035)	(0.035)
county-year shock $_{c,t-1}$*I(B4B) × % of bank type branches with app $_{B4B,c,t}$			-
county-year controls	x	x	x
county FE	x	x	x
year FE	x	x	x
bank type x year FE		x	
observations	19,501	19,501	19,401
R-squared	0.0933	0.115	0.0986

Appendix D - Spectrum Expansions

This appendix details the derivation and usage of the more comprehensive measure of local mobile infrastructure capacity improvements, $spectrum\ expansions_{c,t-1}$.

Derivation. I derive the measure from the universe of Federal Communication Commission (FCC) licenses. The FCC regulates the usage of the *electromagnetic spectrum*, which is the (non-visible) "range of electromagnetic radio frequencies used to transmit sound, data, and video" through devices such as radios, TVs, and smartphones across the country (FCC website). Given the developments in smartphone technology and the growing popularity of mobile communication, the agency has been freeing and dedicating more and more parts of the spectrum—defined in terms of *MHz bands*—to mobile network operators (AT&T, T-Mobile, etc., henceforth MNOs) over the last decade and a half.[28]

The FCC manages the spectrum through a licensing system. An FCC license guarantees the MNO the exclusive use of certain frequencies (i.e., a precise amount of MHz within a MHz band) over a set market area for ten years. The FCC has been allotting these licenses through auctions, frequently auctioning out entire bands at once (i.e., the same amount of spectrum across the country), then letting MNOs outbid each other in every single geography. Once an MNO secures a license through the auction, it can decide when to activate it. Sometimes, activation is immediate, as the MNO just needs to fine-tune antennas to increase transmission capacity. Sometimes, the MNO must expand/ramp up its physical network first, leading to later activation. The license then lasts ten years from the effective date of activation, with options for renewal. Overall, having more licenses (hence frequencies/MHz) translates into being able to better satisfy customers (higher mobile communication capacity).[29]

[28] *MHz* stands for "a unit of frequency equal to one million hertz" (Merriam-Webster). These bands represent the backbone of the roll-out of 3G and 4G technologies.

[29] Different MHz bands serve different purposes in mobile data transfer. However, MNOs use a mix of them to guarantee service across their geographies, and it is safe to assume that more frequencies overall translate into larger operational capacity for the MNO.

In terms of data, the FCC allows the bulk download of all currently active licenses.[30] Active licenses include licenses that have been activated for the first time during the previous ten years and licenses that have been renewed during the previous ten years. While there is no direct distinguishing between the two situations from the data, the FCC mainly auctioned out new MHz bands over the last decade and a half. In particular, the newly granted MHz bands in the 2010-2019 timeframe were the 600MHz, 700MHz, AWS, and 2.5 GHz ones. Notably, the allocation of these new bands led to the quadrupling of the total spectrum devoted to mobile communication in the country in those years. This was an effort by the FCC to address the back-then-booming consumer demand for smartphone communication under the advent of social media and streaming services.[31]

I focused on licenses in the new bands alone and reconstructed the cumulative *spectrum expansions* that happened over time in each county since 2010.[32] In light of the above, these expansions make a good proxy for local increases in mobile infrastructure capacity. As of section 5 onward, the analysis employs the variable $sp.\ expansions_{c,t-1}$ throughout, i.e., county-level mobile spectrum expansions in 100s of MHz since 2010. Panel A of Table 1 reports descriptive statistics for this variable, and Figure Appendix D.1 maps it out over time. The expansions have sped up in the second half of the sample (some important FCC auctions in 2014, 2015, and 2016) and display different paces across different geographies.

Context and use in the analysis. The variable is an extended and detailed version of the more easily computable and previously used $county\text{-}year\ shock_{c,t-1}$, which just considers the

[30]FCC License View.

[31]Source: FCC Auctions Summary, contacts in the industry, and anecdotal evidence. This fact is also reflected in the prices paid by the auction winners, the highest ever (FCC Auctions Summary).

[32]I downloaded FCC license data in 2020, allowing the analysis to go back as far as 2009. For each of the licenses regarding the new bands, I computed the corresponding spectrum amount in MHz (*frequency upper band* - *frequency assigned*, as per FCC definitions) and used the FCC conversion tables between market areas and counties to link it to its counties. I then calculated the total amount of spectrum expansions that MNOs have achieved since 2010 in each county by summing the spectrum amounts across the pertaining new licenses over time, with the minority of licenses that do not span entire counties down-weighted accordingly.

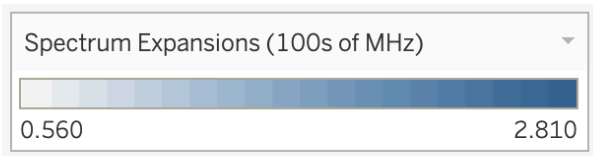
nationwide increases in new mobile spectrum frequencies coming from the biggest auctions of new bands in 2014 and 2016, paired with the local percentage of households with mobile contracts the year prior. Compared to *county-year shock*$_{c,t-1}$, *sp. expansions*$_{c,t-1}$ spans all counties since 2010, considers not only the biggest national auctions but also some minor local ones (deriving from repurposing local TV and radio frequencies), and factors in information on effective license activation times. The latter component is important for the analysis, since in certain areas, the winning-bid MNO activated its newly allotted spectrum license right after winning it; in other areas, it had to build up the physical network first and wait one or two years to activate it. By using year fixed effects and county fixed effects throughout, the analysis effectively targets this rather technical variation. Arguably, it is hard to predict such technical variation even for locals, let alone optimize economic decisions accordingly at the bank level.

Deposit competition on the extended sample. Table D.1 replicates the mobile technology-driven competition analysis of Table 4 using the more complete *sp. expansions*$_{c,t-1}$ measure instead of the rougher and limited in coverage *county-year shock* $_{c,t-1}$ (available only for counties with more than 65,000 residents since 2013). Nonetheless, column 1 of Table D.1 displays the same dynamics of column 1 of Table 4, with the only difference being the standalone coefficient on the technological shock (*sp. expansions*$_{c,t-1}$, representing the effect of the shock on banks that do not provide mobile banking services) not reaching significance. Column 2 shows how this might be a timing effect, whereby the same coefficient and dynamics hold and are significant when using *sp. expansions*$_{c,t}$ rather than *sp. expansions*$_{c,t-1}$. Column 3 further distinguishes between when the app is provided by a small community bank (I(SCB)) *vs* big community bank (I(BCB)) *vs* large bank (I(LB)) *vs* big 4 bank (I(B4B)). Even in the extended sample, providing mobile banking services corresponds to an increase in deposits under heightened local availability and popularity of mobile services, more so at larger and better-digitalized banks. Lastly, column 4 relates growth rates in deposits to $sp.\ expansions_{c,t}$ at active banks. It shows how the technological shock spurs growth at banks with apps but slows it down at banks without apps.

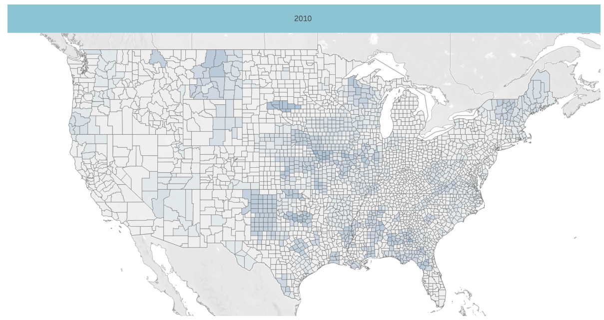
The analysis confirms how the smaller, less-digitalized banks lose deposits and/or exhibit a deposit growth slowdown at times of heightened technological competition with respect to their larger, better-digitalized counterparts. Further, the effect still holds when adding rural areas to the sample, suggesting the effects are not driven by differences and self-selection of geographical nature.

Figure Appendix D.1: **Spectrum holdings over time**

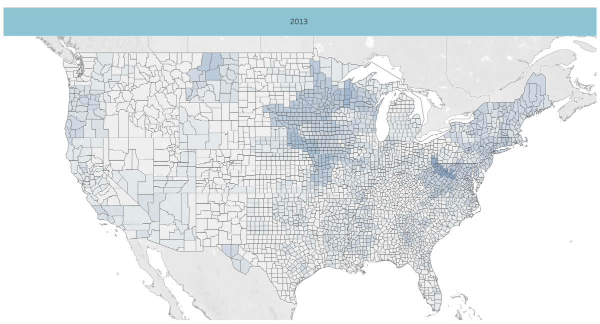
Description: This figure maps Mobile Spectrum Expansions since 2010 across U.S. counties by year.



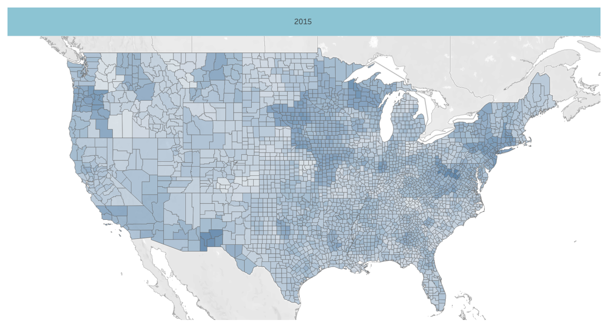
(a) Legend



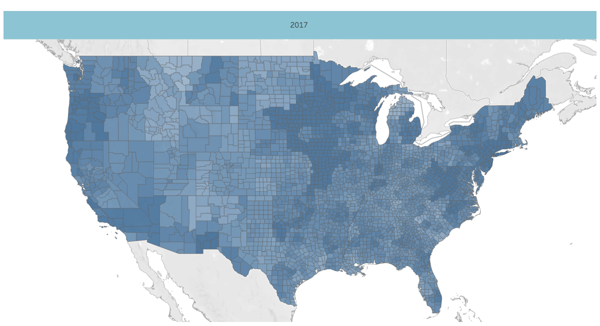
(b) 2010



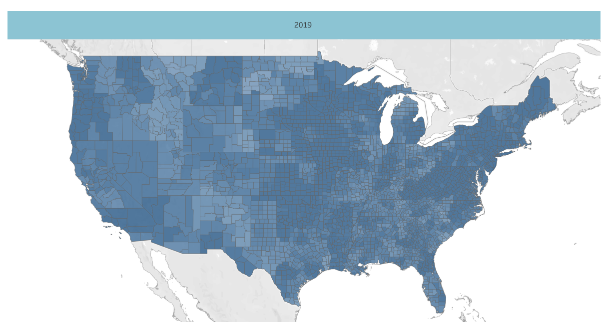
(c) 2013



(d) 2015



(e) 2017



(f) 2019

Table D.1: **Technology-driven Competition on deposits**

Description: This table presents results on technology-driven competition on deposits. The dependent variable in columns 1 to 3 is the natural logarithm of bank b deposits in county c and year t given the bank has an active branch in the county at the time. In column 4 is the difference between the same logarithm of county deposits at time t and the one at time t-1. Across specifications, *sp. expansions*$_{c,t-1}$ capture actual mobile spectrum expansions since 2010 in county c and year t-1 in 100s of MHz. Standard errors are clustered at county level; ***, **, *, $^{+}$ denote 1%, 5%, 10%, and 15% statistical significance; - denotes a coefficient absorbed by fixed effects.

	ln(county deposits$_{b,c,t}$)			Δ ln(county deposits$_{b,c,[t,t-1]}$)
	(1)	(2)	(3)	(4)
sp. expansions$_{c,t-1}$	-0.0144			
	(0.015)			
app available$_{b,t-1}$	-0.121***	-0.149***		-0.291***
	(0.014)	(0.016)		(0.022)
app available$_{b,t-1}$ × sp. expansions$_{c,t-1}$	0.0615***			
	(0.011)			
sp. expansions$_{c,t}$		-0.0252*	-0.0189	-0.0279
		(0.015)	(0.015)	(0.021)
app available$_{b,t-1}$ × sp. expansions$_{c,t}$		0.0710***		0.0454***
		(0.0098)		(0.012)
app available$_{b,t-1}$*I(SCB)			-0.0323	
			(0.020)	
app available$_{b,t-1}$*I(SCB) × sp. expansions$_{c,t}$			-0.000483	
			(0.011)	
app available$_{b,t-1}$*I(BCB)			-0.0267	
			(0.031)	
app available$_{b,t-1}$*I(BCB) × sp. expansions$_{c,t}$			0.0311**	
			(0.016)	
app available$_{b,t-1}$*I(LB)			-0.124***	
			(0.019)	
app available$_{b,t-1}$*I(LB) × sp. expansions$_{c,t}$			0.0740***	
			(0.012)	
app available$_{b,t-1}$*I(B4B)			-0.0909***	
			(0.035)	
app available$_{b,t-1}$*I(B4B) × sp. expansions$_{c,t}$			0.171***	
			(0.021)	
county-year controls	x	x	x	x
bank-year controls	x	x	x	x
county FE	x	x	x	
year FE	x	x	x	x
bank FE	x	x	x	x
observations	254,157	254,157	254,157	254,157
R-squared	0.531	0.531	0.531	0.0779

Appendix E - Small Business Lending by Small Community Banks, county-level

This appendix quantifies 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 bank-county-year level regressions in Table 6) and the loss of lending resulting from SCB branch closures (Table 5). It employs the following year-county-level regression:

$$ln(scb\, SELs_{c,t}) = \alpha_c + \alpha_t + \beta_1\ county\text{-}year\ shock_{c,t-1} + \gamma X_{c,t-1} + \epsilon_{c,t}, \tag{11a}$$

$$ln(scb\, SELs_{c,t}) = \alpha_c + \alpha_t + \beta_1\ spectrum\ expansions_{c,t-1} + \gamma X_{c,t-1} + \epsilon_{c,t}, \tag{11b}$$

where $scb\ SELs_{c,t}$ is the sum of the amount of all commercial and industrial loans below \$1mn and farm loans below \$0.5mn on the balance sheets of SCBs having county c as their main county of operation in year t (Call Report data). In equation 11a the independent variable of interest is $county\text{-}year\ shock_{c,t-1}$, capturing faster implementation of country-wide improvements in mobile infrastructure capacity. In equation 11b the independent variable of interest is $spectrum\ expansions_{c,t-1}$, capturing actual mobile spectrum expansions in county c and year t-1 in terms of the 100s of MHz of new frequencies that have been allotted to the county's mobile network operators since 2010. 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 small community banks branches, population, GDP, income per capita, employment rate, and the number of small businesses.

Table E.1: **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 variable is the the natural logarithm of the total amount of commercial and industrial loans below $1mn plus farm loans below $0.5mn on the balance sheet of small community banks in county c and year t (based on their main county of operation according to deposits). Across specifications, $\textit{county-year shock}_{c,t-1}$ captures faster implementation of country-wide mobile infrastructure improvements policies, and $\textit{sp. expansions}_{c,t-1}$ capture actual mobile spectrum expansions since 2010 in county c and year t-1. The first column has $\textit{county-year shock}_{c,t-1}$ as the main independent variable of interest over its full sample, the second one has $\textit{sp. expansions}_{c,t-1}$ as the main independent variable of interest over the subsample in which the previous $\textit{county-year shock}_{c,t-1}$ is available, the third one has $\textit{sp. expansions}_{c,t-1}$ as the main independent variable of interest over its full sample. Standard errors are clustered at county level; ***, **, * denote 1%, 5%, and 10% statistical significance.

	ln(amount small enterprise loans $_{c,t}$)		
	(1)	(2)	(3)
	full sample	cy-shock subsample	full sample
county-year shock $_{c,t-1}$	-0.313		
	(0.25)		
sp. expansion $_{c,t-1}$		-0.359**	-0.152***
		(0.17)	(0.055)
county-year controls	x	x	x
county FE	x	x	x
year FE	x	x	x
observations	4,476	4,476	20,272
R-squared	0.851	0.852	0.825

Appendix F - Acquisitions Analysis

This appendix focuses on when the adoption of mobile technology is externally imposed. It considers branches that started providing mobile banking services to their customers because they were acquired by banks that were already providing mobile banking services to their customers at the time of the acquisition. Deposit dynamics around mobile infrastructure improvements at these branches are then compared to deposit dynamics at branches that also underwent acquisition but whose acquirer was not providing mobile banking services to their customers at the time of the acquisition. The event window spans from two years before to two years after the acquisition, and the exercise focuses on branches that were run by small community banks at the moment of the acquisition as the most likely to get acquired and to have enough similar branches available for the control group.

Table F.1: **Acquisitions Study**

Description: This table presents results on deposit dynamics around bank branch acquisitions. The sample consists of small community bank branches that have been acquired during the 2010-2019 time frame, and considers from 2 years prior to the acquisition to 2 years after the acquisition. The dependent variable is the natural logarithm of bank b's branch i deposits in county c and year t. The independent variable of interest is $sp.\ expansions_{c,t-1}$ (mobile spectrum expansions since 2010 in county c and year t-1), and its interactions with $post\text{-}acquisition_{i,b,c,t-1}$ and $treated_{i,b,c,t}$. $Treated_{i,b,c,t}$ is a dummy variable equal to one if branch i of bank b in county c and year t is going to or has been acquired by a bank that provides mobile banking services. $Post\ acquisition_{i,b,c,t}$ is a dummy variable equal to one if branch i of bank b in county c and year t has been acquired in year t or t-1 or t-2 by another bank. Standard errors are robust; ***, **, * denote 1%, 5%, and 10% statistical significance.

	(1)
	ln(branch deposits $_{i,b,c,t}$)
sp. expansions $_{c,t-1}$	0.0500
	(0.15)
post-acquisition $_{i,b,c,t-1}$ × sp. expansions $_{c,t-1}$	-0.260*
	(0.14)
treated $_{i,b,c,t-1}$ × sp. expansions $_{c,t-1}$	-0.208
	(0.15)
post-acquisition $_{i,b,c,t-1}$ × treated $_{i,b,c,t-1}$	-0.296**
	(0.12)
post-acquisition $_{i,b,c,t-1}$ × treated $_{i,b,c,t-1}$ × sp. expansions $_{c,t-1}$	0.395***
	(0.15)
county-year controls:	
ln(population $_{c,t-1}$)	-0.647
	(0.69)
ln(# businesses above 100 employees$_{c,t-1}$)	0.0424
	(0.060)
ln(# businesses below 100 employees$_{c,t-1}$)	0.761**
	(0.38)
employment rate $_{c,t-1}$	0.249
	(0.79)
ln(personal income pc $_{c,t-1}$)	0.205
	(0.26)
ln(county GDP $_{c,t-1}$)	-0.148
	(0.15)
bank-year controls:	
ROA$_{b,t-1}$	-2.657
	(1.97)
net interest margin$_{b,t-1}$	-10.48***
	(3.77)
tier 1 lev. capital ratio$_{b,t-1}$	0.00207
	(0.0067)
county FE	x
time FE	x
branch FE	x
observations	15,293
R-squared	0.874

Appendix G - Event Studies

This appendix conducts an event-study analysis around important improvements in local mobile infrastructure capacity. It considers a window from two years before the event to two years after. It defines an event as the county-year pair corresponding to the highest year-on-year % increase in spectrum expansions above 60% for the county. For each such county, it then singles out five untreated (i.e., not belonging to any event window) nearest neighbors the year previous the one of the event based on population, GDP, and income per capita. It then picks the nearest neighbor with the lowest increase in spectrum expansions during the year of the event. It studies how two different county-level outcomes respond to the event. First, it tests whether there are more small community bank net branch closures following the event. Second, it tests whether there is a high drop in small enterprise lending by small community banks following the event.

Table G.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 local mobile infrastructure capacity (> 60% year-on-year increase in mobile spectrum expansions). The event methodology is described in subsection 7.3. 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 on 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%, and 10% 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**	0.0515*	0.0538**
	(0.028)	(0.022)	(0.028)	(0.022)
county-year controls:				
ln(population $_{c,t-1}$)			0.420	-0.436
			(0.43)	(0.51)
ln(# businesses above 100 employees $_{c,t-1}$)			-0.0427	-0.0341
			(0.040)	(0.059)
ln(# businesses below 100 employees $_{c,t-1}$)			-0.132	0.0199
			(0.23)	(0.27)
employment rate $_{c,t-1}$			-0.462	-0.720
			(0.74)	(0.83)
ln(personal income pc $_{c,t-1}$)			0.167	0.211
			(0.15)	(0.18)
ln(county GDP $_{c,t-1}$)			-0.161**	-0.189*
			(0.079)	(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 G.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 the 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.

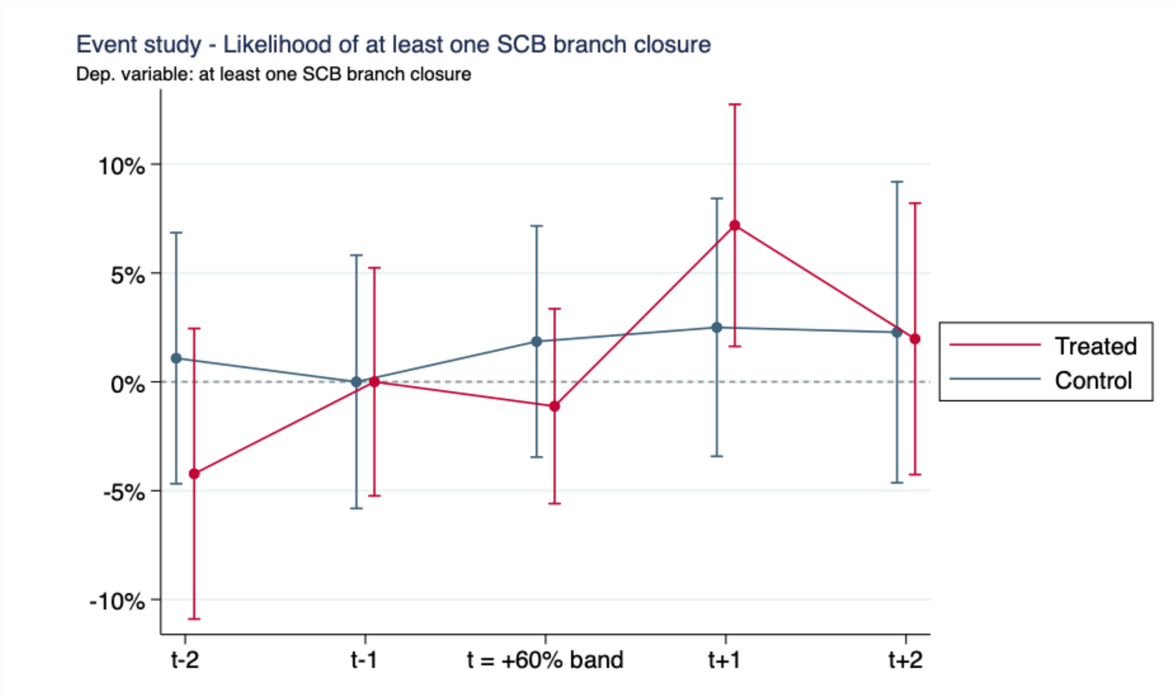


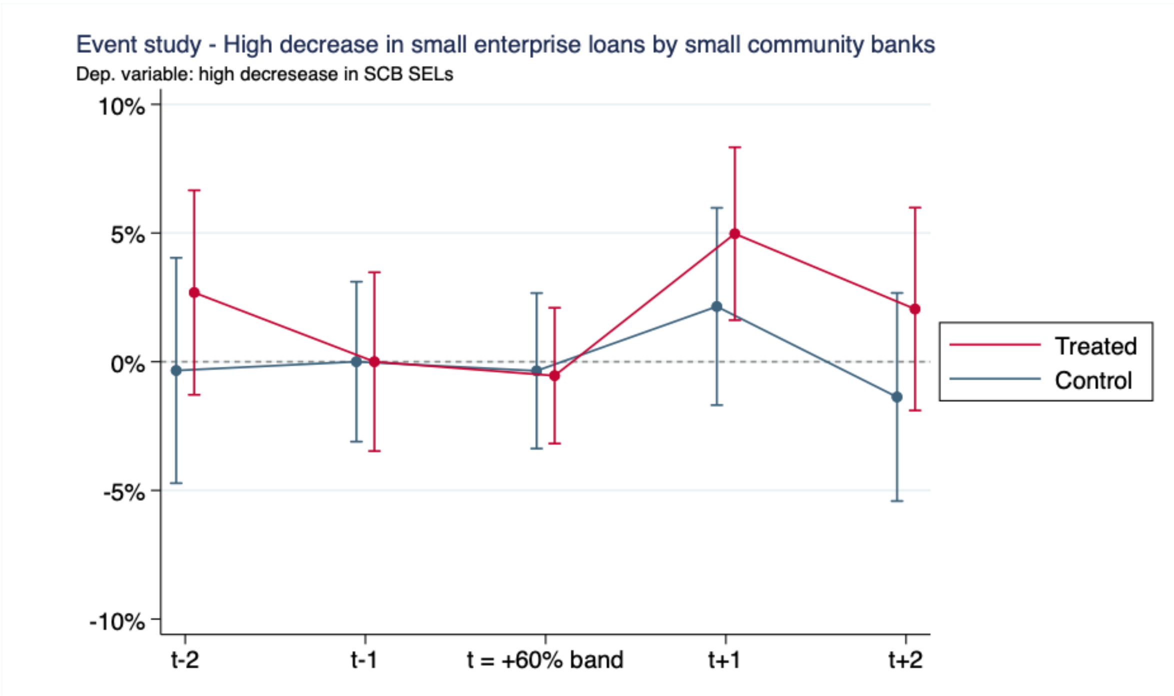
Table G.2: **Event Study: Small Community Bank Small Enterprise Lending**

Description: This table presents results of the event study on small community banks' small enterprise lending (C&I loans<\$1mn + farm loans<\$0.5mn) around high improvements in local mobile infrastructure capacity ($>60\%$ year-on-year increase in mobile spectrum expansions). The event methodology is described in subsection 7.3. 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 enterprise 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 enterpr. lending $_{c,t}$			
	(1)	(2)	(3)	(4)
Treated $_{c,t}$ × Post $_{c,t}$	0.0231	0.0231^{+}	0.0219	0.0231^{+}
	(0.018)	(0.016)	(0.018)	(0.016)
county-year controls:				
ln(population $_{c,t-1}$)			0.184	-0.0554
			(0.31)	(0.45)
ln(# businesses above 100 employees $_{c,t-1}$)			-0.00801	0.0236
			(0.025)	(0.029)
ln(# businesses below 100 employees $_{c,t-1}$)			0.158	0.0848
			(0.16)	(0.26)
employment rate $_{c,t-1}$			-0.479	-1.102*
			(0.37)	(0.59)
ln(personal income pc $_{c,t-1}$)			-0.106	-0.0451
			(0.10)	(0.13)
ln(county GDP $_{c,t-1}$)			0.105*	0.107
			(0.059)	(0.071)
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	0.221	0.615	0.225	0.621

Figure G.2: **Event Study: Small Community Bank Small Enterprise Lending**

Description: This figure plots coefficients of the $Treated_{c,t} \times Post_{c,t}$ interaction variable in the 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.



Appendix H - Economic Consequences by Business Size

Table H.1: **Economic consequences by business size**

Description: This table replicates the real effects analysis of Table 8 by business size. Columns 1, 4, and 7 report estimates for different measures of business growth for businesses with less than 20 employees. Columns 2, 5, and 8 report estimates for businesses with more than 20 employees and less than 50. Columns 3, 6, and 9 report estimates for businesses with more than 50 employees. The dependent variables of interest are the standardized growth rate of the number of relevant businesses in columns 1 to 3, the standardized growth rate of employment at relevant businesses in columns 4 to 6, and the standardized wage growth rate at relevant businesses in columns 7 to 9. Across specifications, *sp. expansions*$_{c,t-1}$ capture actual mobile spectrum expansions since 2010 in county c and year t-1, *SCB deposits*%$_{c,2010}$ is small community banks' deposits over total deposits in county c in 2010. Standard errors are clustered at county level; ***, **, * denote 1%, 5%, and 10% statistical significance; - denotes a coefficient absorbed by fixed effects.

	st. # businesses growth$_{c,t}$			st. employment growth$_{c,t}$			st. wage growth$_{c,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	<20employees	20<empl.<50	>50empl.	<20empl.	20<empl.<50	>50 empl.	<20 empl.	20<empl.<50	>50empl.
sp. expansions$_{c,t-1}$	0.0648*	0.0356*	0.00575	0.0457	-0.0513*	0.0607^{+}	0.110***	0.0605**	0.101***
	(0.035)	(0.021)	(0.020)	(0.035)	(0.030)	(0.038)	(0.031)	(0.030)	(0.035)
SCB deposits %$_{c,2010}$	-	-	-	-	-	-	-	-	-
sp. exp.$_{c,t-1}$ × SCB deposits %$_{c,2010}$	-0.0999***	-0.0594***	0.0195	-0.113***	-0.0455^{+}	-0.0382	-0.101***	-0.0538**	0.00168
	(0.032)	(0.018)	(0.021)	(0.033)	(0.028)	(0.028)	(0.026)	(0.024)	(0.032)
county-year controls:	x	x	x	x	x	x	x	x	x
county FE	x	x	x	x	x	x	x	x	x
year FE	x	x	x	x	x	x	x	x	x
observations	28,081	25,615	21,921	27,708	27,149	26,209	27,708	27,514	26,275
R-squared	0.142	0.113	0.150	0.146	0.0951	0.120	0.0889	0.0733	0.0739

Appendix I - Placebo Tests

Table I.1: **Technology-driven Competition on deposits, Placebo Test**

Description: This table presents results of a Placebo Test on the technology-driven competition on deposits analysis. The dependent variable in columns 1 to 3 is the natural logarithm of bank b deposits in county c and year t given the bank has an active branch in the county at the time. In column 4 is the difference between the same logarithm of county deposits at time t-1 and the one at time t-2. Across specifications, *randomized sp. exp.* are within county and over time randomizations of mobile spectrum expansions since 2010. Standard errors are clustered at county level; ***, **, *, $^{+}$ denote 1%, 5%, 10%, and 15% statistical significance; - denotes a coefficient absorbed by fixed effects.

	ln(county deposits$_{b,c,t}$)			Δ ln(county deposits$_{b,c,[t,t-1]}$)
	(1)	(2)	(3)	(4)
randomized sp. exp.$_{c,t-1}$	0.00198			
	(0.0035)			
app available$_{b,t-1}$	-0.0467***	-0.0502***		-0.253***
	(0.011)	(0.012)		(0.020)
app available$_{b,t-1}$ × randomized sp. exp.$_{c,t-1}$	-0.000983			
	(0.0063)			
randomized sp. expansions$_{c,t}$		0.000145	0.000246	-0.0109
		(0.0031)	(0.0031)	(0.0072)
app available$_{b,t-1}$ × randomized sp. exp.$_{c,t}$		0.00168		0.0230**
		(0.0056)		(0.0095)
app available$_{b,t-1}$*I(SCB)			-0.0801***	
			(0.015)	
app available$_{b,t-1}$*I(SCB) × randomized sp. exp.$_{c,t}$			-0.00515	
			(0.0080)	
app available$_{b,t-1}$*I(BCB)			0.00240	
			(0.022)	
app available$_{b,t-1}$*I(BCB) × randomized sp. exp.$_{c,t}$			-0.0153	
			(0.012)	
app available$_{b,t-1}$*I(LB)			-0.0454***	
			(0.017)	
app available$_{b,t-1}$*I(LB) × randomized sp. exp.$_{c,t}$			0.00908	
			(0.0072)	
app available$_{b,t-1}$*I(B4B)			0.126***	
			(0.034)	
app available$_{b,t-1}$*I(B4B) × randomized sp. exp.$_{c,t}$			0.00735	
			(0.016)	
county-year controls	x	x	x	x
bank-year controls	x	x	x	x
county FE	x	x	x	
year FE	x	x	x	x
bank FE	x	x	x	x
observations	254,021	254,034	254,034	254,034
R-squared	0.531	0.531	0.531	0.0779

Table I.2: **The Asset Side of the SCB Balance Sheet, Placebo Test**

Description: This table presents results of a Placebo Test on the analysis of the impact of the mobile technology shock on the asset side of small community banks' balance sheet. In column 1 the dependent variable is the sum of commercial and industrial loans below \$1mn and of farm loans below \$0.5mn over assets for small community bank b having the majority of its deposits in county c and year t, in column 2 is real estate loans over assets, in columns 3 individual loans over assets. Across specifications, *randomized sp. exp.* are within county and over time randomizations of mobile spectrum expansions since 2010. Standard errors are clustered at the counties covered-year level to correct for potential measurement errors in linking each small community bank to the county it has most of its deposits in (still robust to clustering at county level); ***, **, *, $^{+}$ denote 1%, 5%, 10% and 15% statistical significance; - denotes a coefficient absorbed by fixed effects.

	small enterprise loans o/assets$_{b,t}$	real estate loans o/assets$_{b,t}$	individual loans o/assets$_{b,t}$
	(1)	(2)	(3)
randomized sp. exp.$_{c,t-1}$	0.000292	-0.000274	0.0000712
	(0.00023)	(0.00048)	(0.000087)
county-year controls	x	x	x
bank-year controls	x	x	x
county FE	x	x	x
year FE	x	x	x
bank FE	x	x	x
observations	49,238	49,238	49,238
R-squared	0.861	0.920	0.903

Table I.3: **Real Effects, Placebo Test**

Description: This table presents results of a Placebo Test on the analysis of the real effects of the mobile technology shock accounting for small community bank dynamics. The dependent variables are county GDP growth in column 1, county small businesses' growth in column 2, county small business employments growth in column 3, county small business wage growth in column 4. Small businesses are defined as businesses with less than 50 employees. Across specifications, *randomized sp. exp.* are within county and over time randomizations of mobile spectrum expansions since 2010. Standard errors are clustered at county level; ***, **, *, $^{+}$ denote 1%, 5%,, 10% and 15% statistical significance; - denotes a coefficient absorbed by fixed effects.

	county GDP growth$_{c,t}$	Small Business growth$_{c,t}$	SB employment growth$_{c,t}$	SB wage growth$_{c,t}$
	(1)	(2)	(3)	(4)
randomized sp. exp.$_{\cdot c,t-1}$	-0.00148	0.000244	-0.000178	0.000483
	(0.0011)	(0.00037)	(0.00055)	(0.00066)
SCB deposits %$_{c,2010}$	-	-	-	-
SCB deposits %$_{c,2010}$ × randomized sp. exp.$_{\cdot c,t-1}$	-0.000318	-0.000202	0.000568	-0.000205
	(0.0026)	(0.00090)	(0.0012)	(0.0015)
county-year controls	x	x	x	x
county FE	x	x	x	x
year FE	x	x	x	x
observations	28,076	28,076	27,142	27,506
R-squared	0.215	0.150	0.196	0.0882