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Bank Competition amid Digital Disruption: Implications for Financial Inclusion

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Abstract

This papers studies *how* banks compete amid digital disruption and resulting distributional effects on financial inclusion. Using survey data, we document that digital consumers (younger, more-educated and higher-income) have adapted to mobile banking, whereas non-digital consumers still heavily rely on brick-and-mortar branches. We build a model of bank competition with endogenous branching and entry decisions to show that the shift of digital consumers' preference from branch to digital services affects how banks compete which results in negative spillovers to non-digital consumers. We empirically test the model predictions by exploiting the staggered expansion of 3G networks across the U.S., and our identification strategies rely on difference-in-differences and instrumental-variable (the frequency of lightning strikes) analyses. We find that (1) banks close costly branches, especially in regions with more young people; (2) banks enter new markets with fewer branches which intensifies local competition; and (3) branching banks increase their prices, whereas non-branching banks lower prices. Consequently, non-digital consumers pay a higher cost to access financial services and thus face the risk of financial exclusion. Approximately, this channel causes 2.5 million previously banked individuals to lose banking access. Overall, the evidence highlights the role of banks' endogenous responses to digital disruption in widening digital inequality.

Keywords: digital disruption, bank competition, consumer preference, digital inequality, financial inclusion

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1 Introduction

The impact of financial technology—e.g., mobile banking and online lending—on the banking industry and financial inclusion is central to policy discussions.[1] The widely accepted view is that fintech can democratize access to financial services, increase the competition of financial intermediaries, and improve financial inclusion (Philippon, 2016, 2019). However, survey data reveals a previously overlooked sharp divergence in how consumers access banking services over the past decade: digital consumers (younger, more-educated and higher-income) adapt to digital platforms quickly, while non-digital (older, less-educated and lower-income) still heavily rely on branches (Figure 1-2, IA.1-IA.2).

Motivated by these observations, we study *how* banks compete amid digital disruption and the resulting distributional effect across consumers. Although non-digital consumers still rely on branches, digital disruption has shifted digital consumers' preference from branch services to digital services. As the average preference for branches declines, banks close costly branches, and digital banks enter the market. The intensified competition from digital banks forces incumbents with branches to specialize in the market segment in which they have comparative advantage: branching banks target non-digital customers and exploit market power on them by charging higher prices. Consequently, although digital customers benefit from intensified bank competitions, non-digital customers bear higher costs to access banking services and thus face the risk of financial exclusion. This distributional effect is important with the rising concern about the aging society and digital inequality.

We begin by documenting four stylized facts over the past decade: (1) there was a sharp shift from branch to mobile app as the primary way for bank customers to access banking services, especially for digital customers, (2) bank competition became more national, and local concentration went down, (3) banks closed many branches, and more branch closures were in counties dominated by young population, and (4) more older people became unbanked while more younger people became banked.

Based on the stylized facts, we build a model to study the impact of digital disruption on *how* banks

[1] See, for example, digital devide, digital inequality and United Nation's discussion.

compete and to understand the distributional effect. The basic model framework is in the spirit of Berry, Levinsohn, and Pakes (1995).[2] Our main innovation is to model banks' endogenous branching and entry decisions as they face heterogeneous consumer preference for branch services. On the demand side, consumers obtain banking services characterized by prices, the number of branches, and digital banking quality bundle. Motivated by the stylized facts, we model two groups of consumers, young and old, who differ in their preference for branching and digital services. On the supply side, banks compete to set prices for their services and choose the number of branches which incur costs. As consumers value branch services, banks optimally choose to operate branches and charge markups for their banking services.

Digital disruption shifts older consumers' preference for branch services to digital services, hence lowering the value of brick-and-mortar branches. In response, incumbent banks optimally close some branches. Meanwhile, more banks enter the market with few branches and tailor their strategies to younger consumers. These new entrants increase local competition among banks amid digital disruption. However, older consumers who prefer branch services are left with limited choices. This allows the remaining branches to exploit market power among older consumers. Consequently, digital disruption has a distributional effect on consumer welfare: younger consumers pay lower prices for banking services while older consumers pay higher prices for banking services and are more likely to be excluded from banking services.

To empirically test the model predictions, we exploit the expansion of the third generation of wireless mobile telecommunications (3G) networks. 3G technology allows devices to access mobile multimedia. This technology was the critical infrastructure that popularized mobile applications, including mobile banking. As the 3G infrastructures were slowly constructed in different regions across the U.S., this setting provides us with substantial variations in both the time series and the cross-section.

[2] The discrete choice model by Berry, Levinsohn, and Pakes (1995) has been applied to the banking sector by Buchak et al. (2018); Jiang (2019); Xiao (2020); Benetton (2021); Wang (2020); Robles-Garcia (2019).

We examine how the expansion of 3G networks affects banks' competition dynamics using a staggered difference-in-difference (DiD) framework. First, we establish a significantly positive relationship between the expansion of 3G networks and branch closures at the bank-county level: banks shut down branches in regions with higher coverage of 3G networks. Such effect is robust to the inclusion of bank-county and bank-state-year fixed effects. Consistently, the findings hold true at the aggregate county level: on average, the total number of branches decreases by 8.7% when 3G networks fully cover the county. Moreover, the impact of digital disruption on branch closures is much more salient in counties with more young consumers who have a lower preference for branches.

To address the endogeneity concern that omitted factors drive both 3G network expansion and banking decisions, we further adopt an instrumental variable (IV) strategy, following Manacorda and Tesei (2020) and Guriev, Melnikov, and Zhuravskaya (2021). We use the frequency of lightning strikes per area to predict the expansion of 3G networks. Frequent lightning strikes substantially increase the costs of providing service and maintaining the infrastructure, hence slowing down the rollout of 3G construction. The IV regressions confirm the causal impact of the expansion of 3G networks on branch closures.

Second, we examine whether 3G expansions induce new entries with limited number of branches and increase local competition. To test this prediction, we need to observe banks' activities even if they do not have branches in a region. Thus, we use the Home Mortgage Disclosure Act (HMDA) data, which collects banks' mortgage origination activity in all counties based on the borrowers' location. We find that new entries to the local lending market have fewer branches after the region has access to 3G networks. As a result, the local banking competition increases: Herfindahl-Hirschman index (HHI) index drops and the number of lenders increases. The result is robust to IV analyses using the frequency of lightning strikes.

Third, we study whether banks with local branches charge higher prices relative to banks without local branches as 3G coverage increases— a novel effect of digital disruption on banks' pricing strategies that our model uncovers. We examine both the deposit and the loan pricing. We find that the deposit spreads charged by banks with branches increase with 3G coverage. In the lending market, banks with more branches charge higher loan origination fees as 3G network expands, relative to banks with fewer branches. The result is further corroborated by IV regressions.

As a robustness check, we provide empirical supports for the key model assumption that young and old consumers have heterogeneous preference for branches and the preference further diverges after digital disruption: older borrowers are more likely to choose lenders with branches in their county; and the association between borrower age and the likelihood of choosing a lender with a branch becomes stronger in regions with higher 3G coverage.

The findings collectively suggest that a new banking market structure emerges amid the digital disruption from 3G expansion: banks without competitive advantage in operating branches compete on prices and serve consumers that prefer digital services, whereas banks with competitive advantage in operating branches invest in branches, charge higher prices, and serve consumers that rely on branch services.

Lastly, we establish that the changing landscape of the banking sector has non-trivial impacts on financial inclusion. While younger consumers benefit from 3G expansion, older consumers pay higher prices to access banking services—higher mortgage origination fees and interest spreads—and are more likely to be unbanked in regions with higher 3G network coverage. Moreover, survey data shows that non-digital consumers, including those who are aged, lower-income, and less-educated are more likely to be excluded from banking services after 3G covers their residential area. Importantly, 3G expansion increases older people's unbanked rate primarily by causing those banked individuals to lose banking access. This evidence highlights the essential role of banks' endogenous responses to digital disruption in exacerbating digital inequality, which deserves regulators' attention.

Our paper connects to the growing literature on the costs and benefits of financial technology. This extant literature shows that digital disruption will likely bring in new players, increase competition in the banking industry, and enhance consumers' welfare (Philippon, 2016; Vives, 2019). In terms of the benefits of financial technology, Fuster et al. (2019) highlight that technology increases the speed of mortgage applications without causing higher defaults. Bartlett et al. (2019) document that algorithmic scoring, compared to face-to-face assessment, reduces price discrimination in the lending market. Di Maggio, Ratnadiwakara, and Carmichael (2021) find that the use of alternative data can better assess borrowers' creditworthiness. In terms of the costs, Fuster et al. (2020) find that minorities benefit less from machine learning models. Our paper extends both views by pointing out that digital disruption benefits digital consumers by bringing in new banks. However, the enhanced competition does not benefit non-digital consumers equally, even if digital services are assessible to everyone.

Along this line, we also contribute to the literature on financial inclusion, which discusses that digital divide can be caused by the availability of advanced infrastructures (Philippon, 2019; Saka, Eichengreen, and Aksoy, 2021; Lee et al., 2021), and high transaction costs (Pierre et al., 2018; Jack and Suri, 2014).[3] Amid digital disruption, a rising concern among policymakers is that disparate access to digital services can contribute to persistent social inequality.[4] WorldBank (2016) emphasizes that developing regions do not benefit from new digital technologies owing to the lack of highspeed internet. Our results highlight a new force that can cause digital inequality even in economically developed regions: the endogenous bank responses to consumers' heterogeneous preferences for digital services.

Lastly, this paper contributes to the literature on banking competition (Cetorelli and Strahan, 2006; Garmaise and Moskowitz, 2006; Drechsler, Savov, and Schnabl, 2017; Jiang, 2019; Buchak and Jørring, 2021; Benetton, 2021; Robles-Garcia, 2019). Most of the existing papers focus on banks' price competition; see, for example, Egan, Hortaçsu, and Matvos (2017); Xiao (2020). Our paper adds to this literature by showing how banks' branching decisions interact with pricing decisions when consumers have heterogeneous preferences for branch services. In this regard, we also contribute to the literature that studies the real effect of banks' branch networks (Jayaratne and Strahan, 1996; Huang,

[3] Relatedly, Choi and Loh (2021) show that frictions from closures of ATMs can elicit usage of digital banking.

[4] Many policy discussions about unbanked population. For example, https://www.fdic.gov/analysis/household-survey/index.html, https://www.forbes.com/advisor/banking/costs-of-being-unbanked-or-underbanked/, https://time.com/nextadvisor/banking/what-to-know-if-you-are-unbanked/

2008; Jayaratne and Strahan, 1997; Beck, Levine, and Levkov, 2010). Ménard and Ghertman (2009) and Hubbard and Hubbard (1994) show that branching facilitates diversification of bank portfolios and hence stabilizes banking systems. Carlson and Mitchener (2006) and Kuehn (2018) point out branch banking increases competition, causing the exit of weak banks.

2 Motivating Facts

This section introduces a number of motivating facts about the changes in consumers' preference for bank branches and bank competition as technology develops over the past decade.

2.1 Changes of Ways to Access Banking Service

We begin by showing how consumers access banking services using statistics constructed based on the FDIC Survey of Household Use of Banking and Financial Services. Figure 1 plots the time series and shows a sharp shift from branch to mobile app as the primary way for consumers to access banking services from 2013 to 2019.[5] In 2013, more than 30% survey participants worked with bank tellers at a local bank branch to access banking services. This number declined to about 20% in 2019. Over the same time period, the share of consumers that use mobile app to access banking services increased by about 30 percent, from 5 percent in 2013 to 35 percent in 2019.

This sharp switch to mobile banking happened predominately among young consumers below age 55. Figure 2 panel (a) compares the usages of branch and mobile banking across age groups. As of 2019, senior people rely more on branch, whereas most young people use mobile banking. More than 60% (37-50 percent) of consumers below age 35 (from age 35-54) choose mobile banking as their main way to access banking services, and only less than 10 percent (10-17 percent) choose branch banking as their main way to access banking services. Among consumers with age above 55, there are

[5] Other unreported categories include online banking, ATM, and telephone. We did not include them in the figure to focus on our main message.

more people that choose branch as the main way to access banking services than people that choose mobile banking as the main way to access banking services.

Figure 2 panels (b) and (c) divide the total population into below age 55 and above age 55 and plot the time series evolution of the primary way to access banking series for each group. The usage of mobile banking among people below age 55 rose by 40% from below 10% in 2013 to 50% in 2019. The usage of mobile banking among people above age 55 stayed below 15% in 2019, despite a similar increase from less than 2% in 2013. Figure IA.1 and IA.2 provide parallel evidence that less-educated and lower-income consumers rely more on branches and the more-educated and lower-income consumers prefer mobile banking.

2.2 Geographic Expansion and Increased Bank Competition

Over the past decade, bank competition became more national, and local concentration went down. We use mortgage market as an example since we observe loan applications submitted and processed by almost every lender in the US.[6]

Panel (a) and (b) of Figure 3 compare the distribution of lender geographic presence in 2017 to the distribution in 2009. Lenders have become more geographically dispersed: the entire distribution of the number of counties covered by each lender shifts rightward, and the distribution mass of lender geographic concentration has moved closer to zero (the most geographically dispersed).[7]

The average number of counties covered by each lender increased from 24 to 40, amounting to a 67% increase relative to 2009 average, while the bottom quartile, the median, and the top quartile have increased by 75% (from 4 to 7), 50% (from 8 to 12), and 50% (from 16 to 24), respectively. The average geographic concentration has declined by 26% since 2009. In 2017, there are 896/3128 (29%)

[6] Although the Summary of Deposit database provides branch-level deposit information, there is a crucial issue of using SOD to construct similar competition measures for the deposit market: The information about location is based on branch addresses rather than borrower addresses. Therefore, we do not know the actual number of banks serving each region if some banks serve the region remotely, without a local branch.

[7] Geographic concentration of a lender is calculated as the sum of squared share of mortgage origination activity in each county, i.e., $\sum_k \in \mathbb{K}_i \frac{Volume_{ik}}{\sum_{k \in \mathbb{K}_i} Volume_{ik}}$.

lenders with geographic concentration below 0.2, for example, whereas there are only 592/4282 (14%) lenders with geographic concentration below 0.2 in 2009. These facts suggest that the competition in the mortgage market—the largest consumer credit market—has become more national over the past decade.

As competition becomes more national, local competition has gone up. Panel (c) of Figure 3 presents the entire distribution of county-level HHI index in 2009 and the distribution in 2017, and panel (d) zooms in to the largest 500 counties in terms of total mortgage origination volume. County-level mortgage market HHI indices decrease: the median HHI index drops by 20% from 0.05 in 2009 to 4% in 2017. The reduction in local market concentration is more salient in the largest 500 counties.

2.3 Branch Closure

Banks closed many branches over the past decade. Panel (a) of Figure 4 shows the decline of number of branches over time. The total number of bank branches in the US was more than 95,000 in 2009 and declined to less than 85,000 in 2019.

Moreover, banks closed more branches in counties with more young people. Panel (b) of Figure 4 shows the number of branch closures per bank against county share of population below age 55. The counties with 80% population below age 55 had 2 more branch closures per bank than counties with less than 60% population below age 55.

2.4 Consequence: Unbanked Population

Lastly, while the unbanked population below age 55 has declined over time, the unbanked population above age 55 has been rising since 2010. Panel (a) of Figure 5 plots the time series changes in the unbanked rate by population age. The unbanked rate of population below age 55 dropped by about 4% from 2009 to 2019. Over the same time period, an additional 1% population above age 55 became unbanked. Panel (b) plots the time series changes in the unbanked rate by ownership of phones. The unbanked rate of population with phones dropped by about 2% from 2009 to 2019. Over the same time period, an additional 2% population without phones became unbanked.

2.5 Discussion

We have documented four stylized facts over the past decade: (1) there was a sharp shift from branch to mobile app as the primary way for bank customers to access banking services, (2) bank competition became more national, and local concentration went down, (3) banks closed many branches, and more branch closures were in counties dominated by young population, and (4) more older people became unbanked while fewer younger people became unbanked.

Taken together, these facts are consistent with that changes in young people's preference for branches created negative spillovers to old people by affecting how banks compete. While branch services differentiate individual banks, increasing banks' markup, operating branches is costly. As technological development lowers young people's preference for branches, more banks are able to expand geographically without establishing local branches, and banks also close branches in regions where they used to operate branches. Since they cannot adapt to new technology as quickly, older people are less likely to be financially included.

We formalize this intuition in a model of bank competition in the next section. The model also allows us to study bank competition in a more sophisticated way to understand the distributional effect of technological development.

3 Model

Motivated by the time series trends, we develop a model of bank competition to formally study the distributional effect of technological development through changing how banks compete.

3.1 Setup

3.1.1 Consumer Demand for Banking Services

There are two groups of consumers, young (representing digital) and old (representing non-digital), with a measure μ_y and μ_o and $\mu_y + \mu_o = 1$. consumers, indexed by i, are looking to obtain one dollar worth of banking services, which can be seen as either one dollar of deposit or one dollar of mortgage. They choose among J_T traditional banks ($T-$type) and J_F FinTechs ($F-$type) or stay unbanked. Each option is indexed by j and is characterized by a price, the number of operating branches, and digital banking quality bundle, $\{r_j, b_j, d_j\}$. We denote the unbank decision as choice 0.

The utility consumer type i derives from choosing bank j is

$$u_{i,j} = -\alpha_i r_j + \beta_i b_j + \gamma_i d_j + \epsilon_{i,j} \tag{1}$$

where α_i is rate sensitivity, β_i is preference for branch services, and γ_i is preference for digital banking services. $\epsilon_{i,j}$ is a mean-zero idiosyncratic utility shock, which follows the generalized extreme value distribution with correlation coefficient $\lambda_J \in \{\lambda_T, \lambda_F\}$.[8] λ_T and λ_F are the nested logit coefficients which specify the correlation among bank options within $T-$type and $F-$type banks, respectively. The nested setup assumes that, from consumers' perspectives, $T-$type and $F-$type banks are independent choices while banks within each type have a correlation approximately $1 - \lambda_T$ (or 1-λ_F).

The difference between young and old consumers is threefold. First, old consumers derive more utility from branching services (that is, $\beta_o > \beta_y \geq 0$). This is justified by the fact in Section 2.1 that old people are much more likely to access banking services via a branch than young people. The same fact justifies the second difference between the young and the old in our model: young consumers value digital services but the old do not, (that is, $\gamma_y > \gamma_0 \geq 0$). Lastly, old consumers are less price sensitive than young consumers (that is, $\alpha_y > \alpha_o \geq 0$).

[8] The generalized extreme value distribution has the following cumulative distribution function $F(\epsilon_{i,1}, ..., \epsilon_{i,J}) = \exp\left(- \sum_{t \in \{T,F\}} \left(\sum_{j=1}^{J_t} e^{-\epsilon_{i,j}/\lambda_t} \right)^{\lambda_t} \right)$.

Overall, the utility function features (1) consumers' preference for a lower service price, a higher number of bank branches, and better digital banking quality, (2) heterogeneous preference where young people value digital banking services, whereas old people value more branch services, and (3) banks compete more aggressively within each group than across groups due to the nested structure.

Consumer i chooses bank j if it delivers the highest utility and its utility is also higher than the utility of being unbanked, which is normalized to be 0:

$$u(j; \alpha_i, \beta_i, \gamma_i, \epsilon_{i,j}) \geq u(k; \alpha_i, \beta_i, \gamma_i, \epsilon_{i,j}), \quad \forall k \in 0, 1, ..., J. \tag{2}$$

Given the assumed distribution of $\epsilon_{i,j}$, we can derive a probability that consumer i chooses bank j, which we denote as $s_{i,j}$. Then, the overall demand for bank j's service is characterized as follows

$$D_j = \sum_i \mu_i s_{i,j}, \quad i \in \{y, o\}. \tag{3}$$

3.1.2 Banks

Banks, indexed by j, provide differentiated banking services (i.e., lending or deposit taking) to consumers. They earn revenue from offering banking services and pay to run branches which are valued by consumers.

There are J_T traditional banks ($T-$type) and J_F FinTech banks ($F-$type). Banks within each type are symmetric. $T-$type and $F-$type have the same funding costs, $c_j = c$. They differ in 1) their marginal cost of operating branches and 2) their digital service quality. Traditional banks have a lower cost to operate branches than FinTechs (that is, $\kappa_T < \kappa_F$), while FinTech banks have better digital service quality than traditional banks (that is, $d_T < d_F$). These assumptions are motivated by the empirical facts that traditional banks have sophisticated branch networks, whereas FinTech banks tend to provide services remotely.[9]

Conditional on serving a region, bank j sets the price of its banking services, r_j, and decides the

[9] FinTech banks are broadly defined as lenders with fewer or no local branches.

number of branches, b_j, to maximize their profits:

$$\max_{r_j, b_j} (r_j - c_j)D_j - \frac{1}{2}\kappa_j b_j^2, \tag{4}$$

where D_j is the demand for bank j's banking service, and the second term is the total cost of operating branches.[10] The total bank profit, with the optimal decisions $\{r_j^*, b_j^*\}$, net of entry cost FC_j is

$$\pi_j = (r_j^* - c_j)D_j - \frac{1}{2}\kappa_j (b_j^*)^2 - FC_j. \tag{5}$$

A bank serves a region as long as $\pi_j \geq 0$.

3.1.3 Equilibrium

An equilibrium is a market structure comprising the number of banks of each type, $\{J_T, J_F\}$; the pricing decisions , $\{r_T, r_F\}$; the branching decisions, $\{b_T, b_F\}$; and the market shares, $\{D_T, D_F\}$, such that

1. consumers maximize utility, taking market structure, branching and pricing as given (Equation (2) holds for all consumers);
2. Banks set prices and choose the number of branches to maximize profits, taking market structure and the pricing decisions of other lenders as given (Equation (4) holds for all banks);
3. The number of banks of each type $\{J_T, J_F\}$ is set such that the least profitable bank has a positive π_j and no new bank wants to enter the market (Equation (5) holds true for the marginal bank).

In equilibrium, the likelihood that consumer i chooses bank j with the following probability:[11]

$$s_{i,j} = \frac{1}{J_t} \frac{Z_{i,t}^{\lambda_t}}{1 + \sum_{t \in \{T,F\}} Z_{i,t}^{\lambda_t}}, \quad t \in \{T, F\}, \tag{6}$$

where $Z_{i,t} = \sum_{j=1}^{J_t} \exp(\frac{1}{\lambda_t}(-\alpha_i r_j + \beta_i b_j + \gamma_i d_j))$. The proportion of depositor i stays unbnaked is

$$s_{i,0} = \frac{1}{1 + \sum_{t \in \{T,F\}} Z_{i,t}^{\lambda_t}}. \tag{7}$$

[10] We choose the quadratic cost function such that we can derive interior solution for the number of operating branches.

[11] We derive the equilibrium in the Appendix C.

Given Equation (6), banks' optimal pricing and branching decisions are

$$r_j = c_j + \frac{\sum_{i \in y,o} \mu_i s_{i,j}}{\sum_{i \in y,o} \mu_i \frac{\alpha_i}{\lambda_t} s_{i,j} \left(1 + (\lambda_t - 1)\frac{A_{i,j}}{Z_{i,t}} - \lambda_t s_{i,j}\right)}, \tag{8}$$

$$b_j = \frac{1}{\kappa_j}(r_j - c_j) \sum_{i \in y,o} \mu_i \frac{\beta_i}{\lambda_t} s_{i,j} \left(1 + (\lambda_t - 1)\frac{A_{i,j}}{Z_{i,t}} - \lambda_t s_{i,j}\right), \tag{9}$$

With these expressions, banks' market shares and profits can be derived. Lastly, the entry condition along with the equilibrium profit function yields the number of banks.

3.2 The Effects of Digital Disruption

The emergence of digital banking over the past decade was accompanied by a shift from branch services to digital banking among young people (Section 2.1). Motivated by this fact, we model digital disruption as a preference shock, which simultaneously reduces digital (i.e., young) consumers' preference for branch services and increases their preference for digital banking. Specifically, we link β_y and γ_y to one parameter digital disruption (DD), such that $\frac{\partial \beta_y(DD))}{\partial DD} < 0$ and $\frac{\partial \gamma_y(DD)}{\partial DD} > 0$.

We solve our model numerically as DD increases.[12] Figure 6 shows the effects of digital disruption on how banks compete. The emergence of digital disruption lowers the value of brick-and-mortar branches as a result of a shift of young consumers' preference for branch services to digital services. In response, both types of banks optimally choose to shut down some branches. Interestingly, when DD is large enough, that is, the majority of young consumers shift to digital services, traditional banks start to increase their branches. This is because traditional banks aim to target old customers only and operate more branches to attract them. We will discuss more on this point later. Overall, there is a decreasing trend of total branches operating in the economy, and this rationalizes what we document in Section 2.3. Moreover, as a region becomes more young-consumer dominant (i.e., a bigger μ_y), banks aggregately close more branches after digital disruption as the branch service becomes less valuable for an average consumer. Formally, panel (a) and (e) in Figure 6 show the first prediction:

[12] In our simulation, the parameters we use are $\mu_0 = \mu_y = 0.5$, $\{\alpha_y, \alpha_o\} = \{2, 0.4\}$, $\{\beta_y, \beta_o\} = \{0.8 - DD, 0.8\}$, $\{\gamma_y, \gamma_o\} = \{1.15 \times DD, 0\}$, $\{\kappa_T, \kappa_F\} = \{0.3, 0.35\}$, $c_T = c_F = 0.1$, $\{d_T, d_F\} = \{0, 1\}$, $\{\lambda_T, \lambda_F\} = \{0.4, 0.35\}$, $FC_T = FC_F = 0.08$.

Prediction 1. *The emergence of digital disruption induces banks to shut down branches, especially in regions with more young consumers.*

Before digital disruption, consumers rely on branches, which limits the geographic expansion of banks as operating branches is costly. This limited local competition allows banks to charge high markups.[13] As digital disruption lowers the value of branches, banks with a higher marginal cost of operating branches (i.e., $F-$type banks) are able to attract customers without having a branch, which increases their profitability. Moreover, as more young consumers shift to FinTech banks for better-quality digital services, the aggregate market share of FinTech banks increases. Both the increased profit margin and enlarged market share invites more $F-$type to enter the market. This justifies the increased geographic expansion of banks documented in Section 2.2. That is, digital disruption changes the scope of competition, making it more nationally. As a remark, the new entered $F-$ type bank competes with both types of banks, and the competition is more intense with the same type of bank because of the nested structure of the consumer utility. Formally, panels (b) and (c) in Figure 6 showcase our second prediction:[14]

Prediction 2. *The emergence of digital disruption induces entries of $F-$type banks, which increases the number of banks that serve each region and lowers the market concentration as measured by the HHI.*

Unlike the traditional view, our model shows that these new entries do not lead to a uniform reduction of the prices charged by banks on their services. On one hand, the intensified competition forces $F-$type banks to charge lower prices. On the other hand, as banks close branches after digital disruption, older consumers, who are less adaptive to digital services, are left with limited choices. This allows the remaining branches to exploit market power among older consumers, which induces banks with competitive advantage operating branches (i.e., $T-$type banks) to strategically shift their

[13] Empirically, Philippon (2015) documents that the unit cost of intermediation today is about as high as it was decades ago.

[14] In the numerical simulation, we allow the type of bank with a higher profit (and also higher than the fixed cost) to enter the market first. So the entry of FinTech bank in penal (b) of Figure 6 shows that FinTech banks earn higher profit than traditional banks before the new entry.

focus toward older consumers. As a result, as digital disruption becomes more prevalent, $T-$type banks tend to retain and even increase operating branches (see panel (a)) and exploit market power among older consumers by charging higher prices as these consumers are left with limited branch choices. Formally, panel (d) in Figure 6 shows the third prediction:

> **Prediction 3.** *The emergence of digital disruption leads to diverging pricing behaviors of the two types of banks: $T-$type banks charge higher rates while $F-$type banks charge lower rates.*

Banks' strategic responses to digital-disruption-induced changes in consumers' preferences lead to distributional effects on the young and the old consumers' access to banking services. Young consumers benefit from intensive competition due to new entries of $F-$type banks: both the average service price and the proportion of unbanked young consumers keep dropping as digital disruption spreads. In contrast, on average, old consumers also benefit from the entry of $F-$type banks in the short term as part of them get banking services from $F-$type banks. However, as digital disruption further increases, these older consumers suffer from higher prices charged by $T-$type banks. Consequently, even given the same risk profile, old consumers, on average, pay higher prices for banking services than young consumers, and this poses a risk of financial exclusion on old consumers. Figure 7 shows the distributional effects on the young and the old consumers. We summarize two implications in Prediction 4 and 5:

> **Prediction 4.** *Following digital disruption, young people pay lower prices to access banking services, while old people pay higher prices.*

> **Prediction 5.** *Following digital disruption, the unbanked rate of young people declines, while the unbanked rate of old people rises.*

4 Data

4.1 3G Expansion

3G technology was the key infrastructure that popularized mobile applications including mobile banking.[15] 3G mobile service allows users to freely browse the internet from a smartphone and to access banking services without going to the physical branches. 3G coverage affects bank customers' reliance on bank branches (i) on the extensive margin by affecting the probability of getting banking services via digital channels rather than branches, (ii) on the intensive margin—by affecting the frequency of using bank branches, and (iii) qualitatively—by changing what transactions people do with banks through branches. The qualitative difference that a mobile broadband connection comes from the fact that a number of banking transactions, such as bank account management and transfer, are particularly well-suited for digital access. The ease of connection also makes a qualitative difference by engaging users in mobile banking (Rainie and Wellman 2012). The vast majority of mobile banking users access bank applications via mobile phones, even when these applications can be accessed though a fixed internet connection.

The adoption of 3G technology is staggered. 3G was first introduced commercially in 2001 and considered as the first high-speed mobile network generation with transmitting rates up to 7.2Mbps. According to the International Telecommunication Union (ITU, 2019), the active mobile broadband subscriptions per capita were only 0.04 globally in the 2007 the world but jumped to 0.70 by 2008. In the context of US, the coverage of 3G was 26.7% in 2007, and jumped to 81.4% in 2010. According to the ITU, as of Q4 2012 the USA has 321 million mobile subscriptions, including 256 million that are 3G or 4G. In the cross-section, the coastal areas are early in adopting 3G relative to the central. By 2018, the 3G coverage in the US exceeds 97.7% according to our estimates.

We exploit the timing of 3G expansion in the US as US banks' exposure to technology disruption. Importantly, the most of the growth in individual broadband subscriptions over the past decade, in

[15] Mobile banking before 2010 was most often performed via SMS or the mobile web.

economically developed and undeveloped regions alike, was due to the expansion of mobile broadband internet access rather than fixed broadband (ADSL or fiber-optic cable) access.

4.2 Data Sources

We combine several data sources.

3G Coverage We use digital maps of 3G network coverage from 2007 to 2018 provided by Collins Bartholomew's Mobile Coverage Explorer (Guriev, Melnikov, and Zhuravskaya 2021). These maps gather coverage data that mobile network operators submit to the GSM Association, and essentially provide an indicator variable identifying the availability of 3G for each 1×1-kilometer binary grid cell.[16] To combine data on mobile network coverage with the county-level banking data, we calculate 3G coverage in each county-year as the weighted average of the value of 3G availability weighted by the population density in each grid cell across all grid-cells in each county's polygon.

Bank branch information. The bank branch-level information is extracted from the Federal Deposit Insurance Corporation (FDIC), which is the annual survey of branch office as of June 30 each year for all FDIC-insured institutions. Note that FDIC only insures deposits in banks, so this data does not include FDIC-insured entities, such as credit unions.

Deposit rates. RateWatch provides the interest rates paid on the branch-level deposits. The interest rates paid on branch-level deposits are obtained from RateWatch, which provides weekly deposit rates on products that include certificates of deposit (CDs), and money market accounts, etc. The data are aggregated to the quarterly frequency by averaging the deposit rates for each product of each branch. We focus on $10,000 12-month and 36-month CDs, which are the most popular time deposit product offered across all U.S. branches.

FDIC survey of household use of banking and financial Services. FDIC Survey of Household Use of Banking and Financial Services provides information on consumers' bank account ownership,

[16] If a grid cell is covered by 4G, it is also covered by 3G.

the primary methods banked consumers use to access their bank accounts, bank branch visits, use of prepaid cards and nonbank financial transaction services, and use of bank and nonbank credit. The survey is conducted biennially since 2009. The most recent survey was conducted in June 2019, collecting responses from almost 33,000 consumers. In our analysis, we use surveys in 2009, 2011, 2013, 2015, and 2017.

Lending. We obtain loan-level mortgage origination data from Home Mortgage Disclosure Act (HMDA) database. HMDA includes the vast majority of residential mortgage applications in the United States.

County demographics. County-level demographic features including GDP, population, employment, and per capita income are collected from the BEA. Variables pertaining to real economic outcome are obtained from the Quarterly Census of Employment and Wages; these variables include the annual average of quarterly business establishment counts and of monthly employment.

4.3 Summary Statistics

Our sample period spans the period from 2007 to 2018. We gauge 3G availability in each county-year by calculating the share of the county's territory covered by 3G networks in that year weighted by the population density. Figures 8 show the 3G coverage at the county level across the U.S. in 2007, 2012 and 2018. Lighter shades indicate higher 3G coverage. Evidently, the introduction of 3G is staggered across regions and over time.

Table 1 presents summary statistics for the key variables. To avoid the influence of outliers, all variables (expect for county characteristics) are winsorized at the 1% and 99% level. Panel A of Table 1 reports the variables at the county level. There are large variations in 3G coverage. From Figures 8, we can see such variations come from both time-series and cross-sectional dimensions. Moreover, banks, on average, close 5.7% branches in a county in one year, with an average number of branches per bank of two. In our sample, the number of lenders per county is around 106, and HHI index is 0.09, which indicates a relative competitive market in the local region. Among all lenders, around 47% lenders have branches operating while others provide Online services.

Panel B presents the summary statistics of bank variables at the county level. Consistent with panel A, the statistics show the average number of branches per bank in one county is two. The average spread for 12-month CDs is close to zero, but spreads vary dramatically across banks, from -1.5% to 1.6% in 5% quantiles of both sides. A similar pattern is seen for spreads of 36-month CDs.

Finally, Panel C reports statistics from FDIC surveys across our sample period from 2009 to 2017. The first four columns show the distribution of interviewees: 58.8% are under 45 years old, 41.6% have annul income less than $50,000, 61.4% have college education, and 89.9% have a mobile phone. Overall, there are 28.3% of interviewees accessing banking services through bank tellers, higher than 10.4% of those through mobile banking. However, Figure 1 illustrates a decreasing pattern for the former access but an increasing trend for the latter one. Furthermore, 7.4% of interviewees are still excluded from any banking services. Importantly, within these unbanked consumers, 47.4% of them once had a bank account but turned unbanked.

5 The Impact of 3G Penetration on Bank Competition

This section empirically tests the model predictions 1-3 about the impact of digital disruption on bank competition.

5.1 Branch Closure

5.1.1 Bank-county level evidence

We start with examining how 3G expansion affects branch closures. We first investigate branch closure decisions at the bank level. Bank managers need decide *where* to shut down branches if branches are too costly to operate. Following the intuition of model, it is more efficient to close branches in counties with high 3G coverage and hence low need for branch services. We explore this using a dynamic panel regression:

$$Y_{b,c,t} = \alpha_{b,s,t} + \alpha_{b,c} + \beta 3\text{G Coverage}_{c,t} + \lambda X_{c,t} + \epsilon_{b,c,t}, \tag{10}$$

where b, s, c and t index bank, state, county and year respectively. The dependent variable $Y_{b,c,t}$ records the branch operation status of bank b. Our key variable of interest, 3G Coverage, refers to the share of the population in the region with potential access to 3G. $X_{c,t}$ is a vector of control variables: GDP, per capita income, population at county level. We include these variables to capture the economic development in the ares, which potentially relates to a faster expansion of 3G network. $\alpha_{b,c}$ represent bank×county fixed effects which control for time-invariant characteristics at the bank and county levels, for example, the overall reputation or the initial popularity of banks in certain regions. $\alpha_{b,s,t}$ represent bank×state×year fixed effects which control for time-variant changes at both bank and state levels, including banks' balance sheet information, time-specific shocks at the state level. Including these fixed effects provides a very stringent identification: we mainly exploit the cross-sectional variations in *one* bank's decision to shut down branches in different counties with different accesses to 3G networks within the *same state* in a year. In all specifications, standard errors are clustered at the level of county to account for autocorrelation over time.

Table 2 presents the results of estimating effects of 3G network availability on bank closures under the baseline DiD setting. We adopt two outcome variables: the number of branch closures scaled by last year's total branch numbers and the total branch numbers in log at the bank-county level. The first measurement captures the direct branch closure decisions and the second one ensures that the closed branches are not replaced by new ones. The first four columns confirm that the expansion of 3G networks is indeed associated with banks' decisions to terminate branch operations. On average, the number of branches of one bank drop by 1% after the area is fully covered by 3G networks. The last three columns examine the heterogeneous effects of digital versus non-digital regions which are approximated by the median age of a county. The comparison of (5) and (6) shows that the

3G-induced branch closures mainly concentrate in counties with more young consumers. Column (7) further confirms the statistical significance of such heterogeneous effect.

5.1.2 County level evidence

The above bank-county analysis zooms into decisions of one bank and neglects interbank interactions. Local consumers' access to branch services will not be affected much if new banks with branches enter the market to replace incumbent branches. We then study the impact of 3G coverage on county-level branch closures by aggregating all local banks.

Similar to specification (10), we exploit the effect of getting access to mobile broadband internet using a DiD model with county and state-year fixed effects:

$$Y_{c,t} = \alpha_{s,t} + \alpha_c + \beta \text{3G Coverage}_{c,t} + \lambda X_{c,t} + \epsilon_{c,t}, \tag{11}$$

where α_c is county fixed effects which control for county-specific time-invariant characteristics, and $\alpha_{s,t}$ state×year fixed effects which control for time-specific shocks at the state level. Other details are the same as the specification (10).

The results are reported in Table 3. The results are consistent with the bank-county level analysis. A full coverage of 3G networks in one county, on average, leads to a decrease in the total number of branches by 8.7%. We find significant aggregate negative coefficients in both digital and non-digital counties, but the effect is more salient in the former one. These results further confirm our model predictions.

5.1.3 Event study

To validate the parallel trend assumption, we conduct an event study focusing on sharp increases in county 3G coverage. We define a treatment event as a county's 3G coverage increasing by more than 50% from the previous year. Given the monotonic increasing feature of 3G coverage, such event can happen at most once for one county. For each treated county, we construct a control county if a county has the closest matching score based on county characteristics but did not experience a sharp increase in 3G coverage ever or reach 30% 3G coverage within three years upon the treatment event. We acknowledge that the matching outcome is not ideal because controlled counties are economically less developed than the treated group. However, we show graphically in Figure 9 that there is no pretrend between the two groups. Focusing on the sample constructed, we estimate a DiD specification as below:

$$Y_{cohort,c,t} = \alpha_{cohort,t} + \alpha_{cohort,c} + \beta \text{Treat} * Post + \lambda X_{c,t} + \epsilon_{cohort,c,t}, \tag{12}$$

where Treat refers to the treatment counties with sharp increase in 3G coverage. We consider a five-year window around the treatment year [-2, -1, 0, 1, 2], and assign Post to be 1 if the event year is ≥ 0 and zero otherwise. We use *cohort* to indicate the matched group for each treated county. The analysis compares county-level number of branches between the treated and control groups within a window around the event that counties experienced a sharp 3G coverage increase.

We report the results in Table 4 and illustrate dynamic differences between the two groups in Figure 9. The coefficients on the interaction term Treat×Post are significantly positive when explaining the proportion of branch closed and are significantly negative for the number of local branches. From the figure, it is clear that the treated counties start to experience significant branch closures at the time of sharp 3G networks expansion and this effect got stronger over the years. In contrast, the differences during the 3-year pre-event window are small in magnitude and statistically indistinguishable from zero. Hence, there exit no pretrends.

5.1.4 IV analysis

Finally, we adopt the IV approach proposed by Manacorda and Tesei (2020) to overcome the difficulty that our DiD specification can not control for all unobserved factors driving 3G networks and banks' decisions.

We construct the population-weighted frequency of lightning strikes per square kilometer, and use it to predict the speed of 3G expansion, following Guriev, Melnikov, and Zhuravskaya (2021); Manacorda and Tesei (2020). The identification assumption is that the frequency of lightning strikes affect banking decisions in the local region only through its impact on the expansion of 3G networks. The relevlent condition between lightning spikes and the speed of 3G network expansion has been verified by multiple studies (Andersen et al., 2012). Frequent lightning and the resulting electrostatic discharges can damage the infrastructure for mobile coverage and negatively affect the transmission of signals. These negative impacts reduce the profits of service providers as power protection and maintenance are costly and increase the risk of intermittent communications. Therefore, we expect that areas with more lightning incidents have lower supply and slower adoption for 3G networks. The exclusion restriction is likely to be valid in our context because banks' decisions to close branches are unlikely driven by weather conditions.[17]

The first stage of IV regression is specified as follows:

$$\text{3G Coverage}_{c,t} = \alpha_{s,t} + \alpha_c + \mathbb{1}(\text{High Lightning}_c) * t + \mu Z_{c,t} + \epsilon_{c,t}, \tag{13}$$

where $\mathbb{1}(\text{High Lightning}_c)$ is an indicator variable which equals to 1 if the county c's average population-weighted frequency of lightning strikes across 2007 to 2018 is higher than the sample average, and 0 otherwise, t is year, and $Z_{c,t}$ include all control variables. We interact lightning strikes with a time trend as the prediction variable to captures the monotonic growth feature of 3G coverage, following Guriev, Melnikov, and Zhuravskaya (2021). Moreover, to take into the consideration that the initial status of 3G networks in our sample may affect the speed of expansion we add the interaction term of time trends and county-level 3G coverage in 2007. We then estimate the second stage using predicted county-level 3G coverage.

The tight relationship between frequency of lightning strikes and 3G coverage is confirmed in column (1) of Table 5. The estimated Cragg-Donald Wald F statistic is 107.90, much higher than the

[17] Maybe extreme weathers may affect banks decisions' to open branches in an area. For example, if perennial bad weathers force local residents to rely on vehicles going out, banks may choose to locate their branches sparsely. However, given they have established branches, we do not see a reason to link closure decision to weather conditions.

1% significance critical value Stock-Yogo weak ID test. In the second stage, we repeat the analysis for most stringent specifications for bank-county level and county level using the projected 3G coverage from the first stage regression. The results in the last four columns of Table 5 are well consistent with other results: 3G expansion results in a significant decline in the number of bank branches. Moreover, the magnitude of the IV estimates is substantially larger than those in Table 2 and 3. One potential explanation is that consumers in regions with frequent lightning strikes may favor benefits brought by 3G networks more, and in response, banks close branches more aggressively in these regions.[18]

Overall, the results we present in this section strongly suggest that the impact of 3G networks on banks' decision to shut down branches can be interpreted as causal.

5.2 Form of Entry and Geographic Expansion

Model prediction 2 suggests that digital disruption induces new entries with limited number of branches. To test this prediction, we need to be able to observe banks' activities even if they do not have branches in a region. The FDIC branch-level dataset used in the previous section could not serve this purpose. Thus, we adopt the HMDA data, which collects banks' mortgage origination activities in all counties based on the borrowers' location. We examine how 3G penetration affects the way banks operate in a market and enter a new market. We estimate the following specification at the bank-county-year level:

$$Branch_{b,c,t} = \alpha_{b,c} + \alpha_{b,s,t} + \beta \text{3G Coverage}_{c,t} + \lambda X_{c,t} + \zeta B_{b,c,t} + \epsilon_{b,c,t}, \qquad (14)$$

where $Branch_{b,c,t}$ is an indicator for whether bank b has a branch in county c in year t or the logarithm of one plus the number of bank b's branches in county c in year t, 3G Coverage$_{c,t}$, $\alpha_{b,c}$ and $\alpha_{b,s,t}$ have been defined under specification (10). $X_{c,t}$ is a set of county controls including log income per capita, log county GDP, and log total population, and $B_{b,c,t}$ is a set of bank-county controls including the amount of mortgages and refinancing loans originated. The inclusion of county economic controls

[18] In such a case, IV regressions effectively estimate the *local* average treatment effect (ATE) in regions with frequent lightning strikes, whereas OLS regressions estimate the ATE over the entire sample.

and fixed effects allows us to identify the effect of 3G penetration by the variation of decisions for the same bank in the same state in the year demeaned at the bank-county level.

Table 6 reports the results. As 3G enters and covers the entire region, the number of branches a bank has in regions where it originates mortgages declines by 2% (column (1)). In column (2) we instrument 3G with lightning strikes frequency and confirms the result in column (1) that 3G coverage causally reduces banks' propensity of using branches when originating loans. In columns (3)-(4), we zoom into the subsample of new entry banks which did not originate loans in the county in the past year. As 3G covers the entire region, entrants have 0.5% fewer branches (column (3)). In columns (4), we instrument 3G with lightning frequency and confirms the result in column (3) that 3G coverage causally reduces banks' propensity of replying branches when entering a new county. These results confirm Prediction 2 that the emergence of digital disruption induces entries of banks with fewer branches ($F-$type banks).

5.3 Local Competition

We then examine whether 3G penetration increases local competition as stated in model prediction 2. We estimate equation 11, where the outcome variables are two county-level competition measures: Herfindahl-Hirschman index (HHI) and the log number of lenders serving the region.[19]

Table 7 reports the results. In this table, we construct the measures using all types of lenders to better estimate market competition. Columns (1)-(4) include all loans. Across all loan products, we find that local competition increases as 3G penetrates a region. Increasing 3G coverage from 0 to 100% reduces HHI by 37.9 bps. Relative to the median county HHI, the effect translates into an economically meaningful 5.8% reduction in concentration.[20] Also, the expansion of 3G is associated

[19]
$$HHI_{ct} = 10000 \times \sum_{l \in L_{(c,t)}} S_{lct}^2$$
where $S_{l,c,t}$ denotes the market share of lender l in county c and year t, and $L_{(c,t)}$ is the set of lenders that originated loans in county c and year t.

[20] County median HHI is 648.8 bps.

with more banks serving a region. Quantitatively, as 3G coverage increases from 0 to 100%, a region is served by 3.8% more banks, amounting to additional 3 banks.[21] Columns (3)-(4) confirm the finding in columns (1)-(2) with 3G coverage instrumented by the lighting strikes frequency.[22]

In Appendix Table IA.3, we use only bank lenders for the construction of HHI and number of bank lenders and obtain similar results. This suggests that the effect of 3G penetration on competition is not completely driven by the expansion of FinTech non-bank lenders: many banks are able to expand to regions outside their branch networks after 3G penetrates those regions.

Overall, the empirical evidence supports the model prediction 2 that after 3G expansion, more FinTech banks enter the market, leading to more intense competition.

5.4 Pricing

Our model uncovers a novel effect of digital disruption on banks' pricing strategies, as stated in 3. We next take it to the data and study whether Banks with local branches charge higher prices relative to banks with fewer or no local branches as 3G coverage increases. We examine both the deposit pricing and the loan pricing.

5.4.1 Deposit Pricing

Due to data availability, we only observe the deposit rates charged by banks in counties where they have local branches. Therefore, our test for deposit pricing focuses on the pricing strategies of banks with local branches ($T-$ type bank in the model) and examines whether these banks charge higher prices after 3G coverage increases. Formally, we estimate the following specification:

$$DepositSpread_{b,c,qt} = \alpha_{b,c} + \alpha_{s,qt} + \beta 3\text{G Coverage}_{c,t} + \lambda X_{c,qt} + \epsilon_{b,c,qt}, \tag{15}$$

[21] The sample median number of lenders in a county is 74.

[22] We zoom into refinancing loans and home purchase loans in Appendix Table IA.2, and we see consistently results that 3G coverage leads to more lenders operating in a market and hence more fierce competition. Interestingly, the effect on HHI is particularly stronger for refinancing loans, and one possible reason is that refinancing loans can be better handled by FinTech, compared to home purchase loans.

where $DepositSpread_{b,c,qt}$ is the spread between 3-month federal fund rates and deposit rates charged by bank b in county c in quarter qt, and the remaining variables are the same as the ones in equation (10). This specification exploits the deposit pricing variations of different banks in different counties of the same state in a year demeaned at the bank-county level.

Table 8 reports the results. Columns (1) and (4) estimate a less saturated specification without bank×county fixed effects. Columns (2) and (5) estimates equation (15). Columns (3) and (6) instrument 3G coverage with lighting strikes frequency in estimating equation (15). As 3G coverage increases from 0 to 100% in one county, spread of 12-month CDs is priced 2 bps higher by banks in this county than those in other counties without 3G coverage from the same state. The effect is relatively weaker for 36-month CDs, but the signs in columns (4)-(6) are consistent with our prediction.

5.4.2 Loan Pricing

To further examine the pricing strategy of $F-$type banks, we turn to the loan pricing data. Consumers pay two types of prices to obtain a mortgage loan: upfront origination fees and loan interest rates. Since 2018, HMDA starts collecting loan-level interest rates and fees, along with other information about loan and borrower characteristics. We examine the impact of 3G expansion on these two types of prices by estimating the following specification:

$$\begin{aligned} Price_{b,j,c} = {} & \alpha_c + \alpha_s + \alpha_b + \beta \text{3G Coverage}_c \\ & + \gamma \text{3G Coverage}_c \times \text{Branch}_{b,c} + \zeta \text{Branch}_{b,c} + \delta Loan_j + \epsilon_{b,j,c}. \end{aligned} \tag{16}$$

Since the test sample focuses on 2018 only, we drop the time subscript t in this loan-level specification. $Price_{b,j,c}$ is price charged by bank b in county c to borrower j, 3G Coverage$_c$ has been defined above, $Branch_{b,c}$ is an indicator for whether bank b has a branch in county c or the logarithm of one plus the number of bank b's branches in county c, and α_c, α_s and α_b are county, state and bank fixed effects, respectively. The inclusion of county and bank fixed effects allows us to identify the impact of 3G penetration by exploiting variations of banks' pricing decisions within a county after taking out banks' average pricing across the US. $Loan_j$ is a set of borrower-loan controls including the natural logarithm of loan size, loan type (i.e., conventional, FHA, VA, or RHS), loan purpose (home purchases, refinancing or others), loan-to-value ratios, debt-to-income ratios, and borrowers' income in natural logarithm, gender, age, and race.

The object of regression (16) is to compare whether the pricing strategy of $T-$type banks—banks with (or with more) branches—differs from the strategy of $F-$type banks—banks without (or with fewer) branches. Table 9 reports the results. The outcome variable in Panel A is loan origination fees. The outcome variable in Panel B is mortgage interest rate. All columns include lender fixed effects. Odd columns include state fixed effects, and even columns include county fixed effects. In columns (1)-(2), the key independent variable of interest is the interaction term between 3G coverage and an indicator variable for the lender bank having a branch in counties where it has borrowers. Columns (3)-(4) have the interaction term between 3G coverage and the natural logarithm of one plus the number of branches of the lender bank in counties where it has borrowers.

Consistently, Panel A of Table 9 shows that 3G has a sizeable impact on decreasing the loan fees: a full 3G penetration leads to a 0.603% (=0.729%-0.126%) reduction in non-branching banks' origination fees in column (1). Such dampening effect is mitigated if loans are originated by banks with branches in a county, supported by positive coefficients of the interaction term across four specifications. The intuition is in line with the model illustration that banks with branches are more differentiated following 3G expansion and hence do not decrease fees as much as non-branch banks do.

Panel B of Table 9 reports little evidence suggesting 3G coverage affects interest rates—coefficient estimates on 3G coverage are insignificant. Moreover, the marginally negative coefficient estimates on the interaction terms suggests that the interest rates do not significantly vary with banks' provision of branches in the local market.[23] Although the loan pricing effect mainly stems from the origination

[23] Consistent with our findings, Buchak and Jørring 2021 find that the market concentration affects fees substantially but has no detectable impacts on interest rates using HMDA 2018-2019 datasets.

fees rather than interest rates, the findings are still economically meaningful given that the former accounts for almost one half of the latter and also contributes substantially to the overall loan costs born by borrowers.

Overall, we find consistent empirical evidence with the model prediction that 3G reduces deposit and loan pricing because it lowers the operating costs of different types of banks. Importantly, the diverging consumer preference for branches gives banks with branches an edge which allows these banks to charge relatively higher deposit and loan prices vis-à-vis non-branch banks after 3G expansion.

5.5 Validity of Model Assumption

Our key model assumption is that young and old consumers have heterogeneous preference for branches and digital services and that their preferences change after the digital disruption. This section provides empirical supports for this assumption.

Figure 2 has shown that users above 55 rely on branches rather than mobile apps to access banking services, and the opposite is true to those below 55. To corroborate this motivating fact, we provide statistical analysis using FDIC Survey of Consumers Use of Banking and Financial Services. Specifically, we relate respondents' answers to the question "most common way to access account" to their age and the 3G coverage in their residence areas.[24] Column (1) in Table 10 shows that consumers under 45 years old choose mobile banking over branches than those above 45, which is consistent with Figure 2. This heterogeneous preferences is amplified by digital disruption, as evidenced by columns (2) and (3). The positive coefficients on the interaction term between 3G coverage and young dummy suggest that young consumers shift towards mobile banking whereas old consumers shift towards branches after 3G expands to their residence areas. The diverging preference is robust to including MSA×Year fixed effects (column (3)).

We then further validate the assumption by focusing on the lending side and relate borrowers'

[24] There are six choices for the question: "Bank teller," "ATM/Kiosk," "Telephone banking," "Online banking," "Mobile banking," and "Other," and interviewees can only choose one answer.

choices between lenders with and without branches to borrower age. Table 11 presents the results of loan level regressions using all loan applications recorded in HMDA 2018:

$$
\begin{aligned}
Branch_{b,j,c} &= \alpha_c + \alpha_s + \alpha_b + \beta 3\text{G Coverage}_c + \zeta \text{Borrower Age}_j \\
&\quad + \gamma 3\text{G Coverage}_c \times \text{Borrower Age}_j + \delta Loan_j + \epsilon_{b,j,c}, \qquad (17)
\end{aligned}
$$

where $Branch_{b,j,c}$ is an indicator variable that equals one if borrower i gets loan loan from bank b which has at least one branch in county c, $BorrowerAge_j$ are a set of indicator variables for borrowers' age range, and other variables are defined in Equation 16.

In columns (1)-(2) of Table 11, we examine whether a borrower's age group affect her choice of lenders with respect to whether lenders have a branch in her county. In terms of coefficient estimate size, the order of the coefficient estimates on the age group dummies parallels that of age group. This order is preserved when we include loan-, borrower- and lender-level characteristics, county fixed effects, and lender fixed effects. Overall, older borrowers are more likely to choose lenders with branches in their county.

In columns (3)-(4), we interact these age group dummies with 3G coverage. The increasing positive coefficient estimates from the interaction term from young to old borrowers illustrate that 3G coverage further lowers young consumers' preference for branches relative to old consumers' preference.[25]

Lastly, if the preference for branches reduces by similar amount for young and old consumers after 3G expansion, the reduction in the aggregate market share of all lenders with branches would be homogeneous across counties with different compositions of young and old consumers. We reject this null hypothesis in Table IA.5 by showing that after 3G expansion, the aggregate market share of lenders with branches experience a sharper decline, especially in counties populated by more young consumers. This further supports that the 3G expansion has a profound impact on the way consumers access to banking services.

[25] Regarding the flipping signs of the baseline coefficient estimates on age groups, 3G coverage is on average 0.6 in our sample and hence the overall average effect of age groups beyond 35 are still positive for choosing lenders with at least one branch.

Overall, the results are consistent with heterogeneous preference changes across young and old consumers following 3G expansion.

6 The Distributional Effects

This section tests the model predictions 4-5 about the distributional effects of digital disruption across the digital and non-digital population.

6.1 Intensive Margin: Banking Service Cost

We begin by testing the effect of 3G expansion on the costs paid by young consumers and by old consumers to access banking services as stated in model Prediction 4. To this end, we exploit within county variation by comparing the average loan origination fees and interest rates paid by different age groups following the expansion of 3G network.[26] Formally, we estimate the following specification:

$$\begin{aligned} Price_{b,j,c} = \alpha_c + \alpha_s + \alpha_b + \beta \text{3G Coverage}_c + \zeta \text{Borrower Age}_j \\ + \gamma \text{3G Coverage}_c \times \text{Borrower Age}_j + \delta Loan_j + \epsilon_{b,j,c}, \end{aligned} \tag{18}$$

where $BorrowerAge_j$ are a set of indicator variables for borrowers' age range, and other variables are defined in Equation 16. The independent variable of interest is the interaction term between 3G coverage and indicator variables for borrowers' age range. The inclusion of loan characteristics and fixed effects allows us to identify the differential effect of 3G penetration on old versus young borrowers while accounting for other loan, borrower, bank and county characteristics.

Table 12 reports the results.[27] In columns (1)-(2), we examine the effect of 3G coverage on loan origination fees. In column (1) where we include state and bank fixed effects, the coefficient estimate on 3G coverage is significantly negative, suggesting that on average 3G reduces origination fees for borrowers younger than 35, which is our reference group. The positive coefficient estimates on the

[26] We do not have data on depositor characteristics, and hence focus on borrowers in this section.
[27] This table includes only bank lenders and Table IA.6 includes loans originated by all types of lenders.

interaction terms of *34<Borrower Age<55×3G Coverage* and *54<Borrower Age×3G Coverage* imply that older borrowers pay higher loan origination fees on average, compared to the reference group. In particular, the coefficient magnitudes of the interaction terms increase with age too—0.213 for the 34-55 group versus 0.543 for the 55 above group. Such ranking holds true if we further incorporate county fixed effects in column (2). This result suggests that older people pay higher prices compared to younger people for accessing loans following the digital disruption of 3G.

In columns (3)-(4), we examine the effect of 3G coverage on mortgage interest rate. Consistent with column (1), the coefficient estimate on 3G coverage is negative in column (3) and thus indicates that 3G expansion lowers loan interest rate for the reference group. In both columns, the coefficient estimate on the interaction term *34<Borrower Age<55×3G Coverage* remain positive statistically significant, which suggests that borrowers between 34 and 55 years old pay higher loan interest rate than borrowers below 35. For the 55 above group, the coefficient estimates on the interaction term are marginally positive.

Overall, borrowers above 35 pay more loan interest rate than those below amid the 3G digital disruption. Compared to columns (1)-(2), the economic and statistical significance in columns (3)-(4) both drop. This pattern is consistent with Table 9 that 3G impact is more pronounced for origination fees than interest rates.

6.2 Extensive Margin: Unbanked

In this section, we test the model prediction 5 that the unbanked rate of digital consumers declines, while the unbanked rate of non-digital consumers rises following the 3G expansion. This analysis also helps shed light on how the digital disruption of 3G influences financial inclusion and digital inequality.

We unmask the differential implication of 3G coverage on banking access across demographic groups using FDIC Survey of Consumers Use of Banking and Financial Services. In Table 13, the dependent variable is an indicator variable which equals one if the respondent does *not* have access to any banking services. The survey only records the MSA location of a respondent. Correspondingly, we aggregate 3G coverage to the MSA level as the weighted average of the value of 3G availability weighted by the population density in each MSA's polygon. All columns control for MSA and year fixed effects. In addition, even columns also include MSA-year fixed effects to account for local economic development confounders.

We interact 3G coverage with an indicator variable for respondents who are younger than 45 (columns (1)-(2)), earn less than $50,0000 annually (columns (3)-(4)), have college education (columns (5)-(6)), and have a phone (columns (7)-(8)). The respective coefficient estimates of the interaction term across these columns suggest that the exacerbating effect of 3G coverage on being unbanked are more pronounced for those respondents who are older than 45, lower-income, less educated, and without cellphones.

Importantly, the significantly positive coefficients on 3G coverage in columns (1), (5) and (7) show that 3G expansion induces more old, less-educated, and no-phone consumers to become unbanked, suggesting that these consumers get strictly worse off (rather than compared to their counter-parities) after digital disruption. To further support this point, we show in column (9) that a 100% coverage of 3G network increases old people's rate of losing banking access (from banked to unbanked) by 1.9%. This effect is approximately 50% relative to the average rate of losing banking access. Moreover, this estimated coefficient is very similar to that in column (1), suggesting that the 3G expansion negatively affects old people primarily by turning them from banked to unbanked. This evidence highlights the essential role of banks' endogenous response to digital disruption in affecting digital inequality. Our new channel sheds light on the puzzling fact that some banked households can become unbanked amid digital disruption.

That is to say, the digital disruption renders non-digital consumers at the risk of being excluded from banking services. This result in particular deserves regulators' attention.

7 Conclusion and Discussion

In this paper, we provide a theoretical framework to analyze how digital disruption (e.g., mobile banking and online lending) affects consumers preference, banks' branching decisions, the resulting competition dynamics and digital inequality. We empirically test model predictions by exploiting the staggered expansion of 3G networks across the U.S., and by further instrumenting 3G coverage with the frequency of lightning strikes to establish causality. we show that after 3G expansion: 1) banks shut down costly branches, especially in regions with more digital consumers; 2) new entry from banks with fewer branches intensifies the local competition; 3) banks with (without) branches charge high (low) prices. As a result, non-digital consumers who prefer brick-and-mortar branches have to pay a higher cost to access financial services and are subject to the risk of financial exclusion. Overall, this paper highlights a new banking channel of digital inequality.

This paper speaks to several prevailing policy discussions. Our results highlight that the benefit of digital disruption may come at the cost of consumers with certain types of preferences, which receives less attention in the current discussion of how technology shapes banking. We also bring in a new perspective of customer diverging preference and product differentiation in analysing how technology affects bank competition, which is missed in the current discussion. Importantly, we also calibrate the consequences of digital disruption in terms of financial inclusion and potential price discrimination. By unraveling the heterogeneous consumer and bank type, we hope this paper can provoke new insights as to the interaction between technology and financial intermediaries.

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A Figures

Figure 1: Change of Ways to Access Banking Services

The bar chart shows time series of the primary ways consumers access banking services from 2013 to 2019. Source: FDIC Survey of Household Use of Banking and Financial Services.

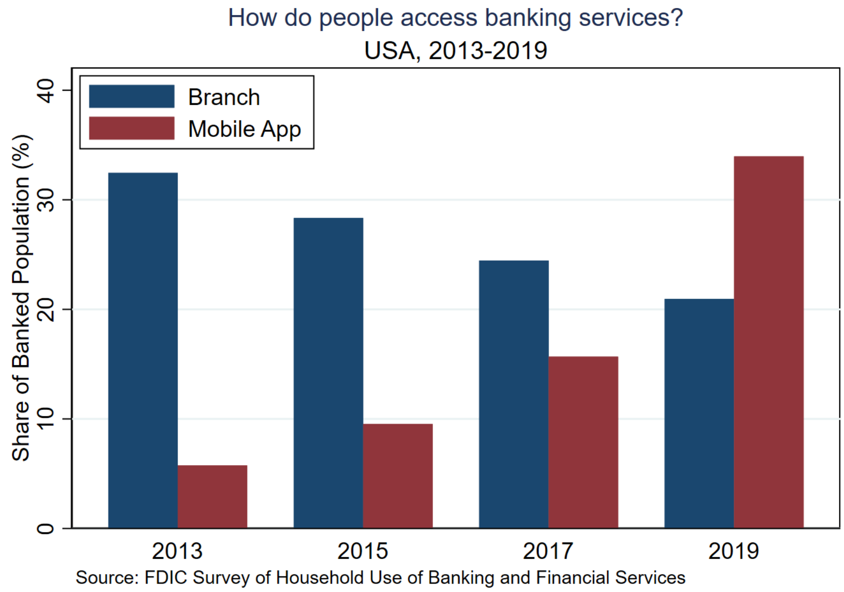
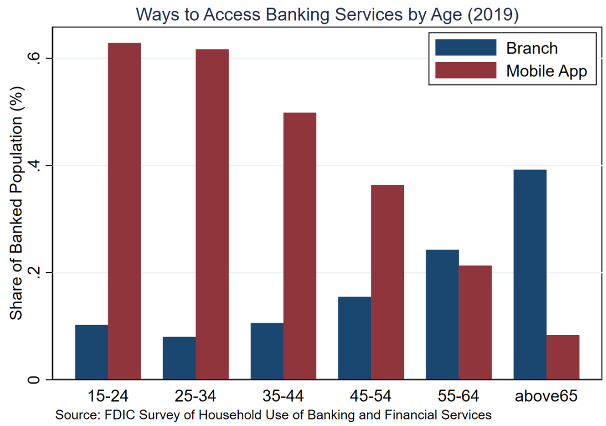
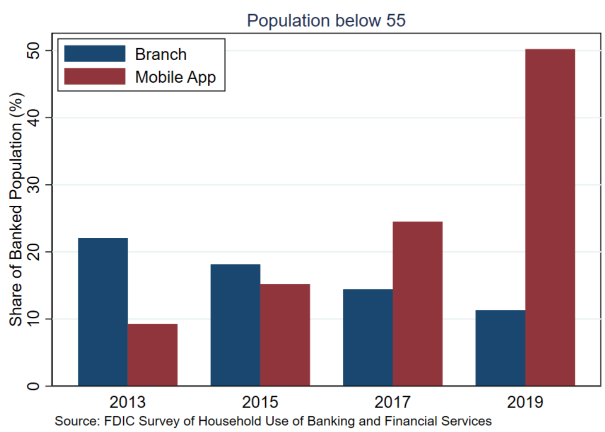


Figure 2: Change of Ways to Access Banking Services—by Age

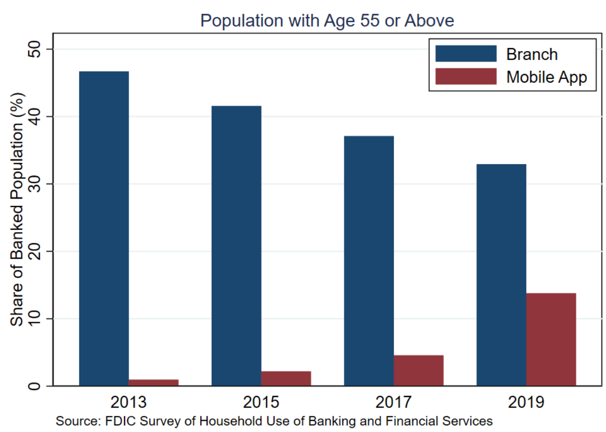
The bar charts show the ways consumers in different age buckets to access banking services. Panel (a) plots the share of survey participants that access banking services via branch and via mobile app across age distribution in 2019. Panel (b) and (c) plot the same time series for young and old consumers, defined as below or above 55-year old, respectively. Source: FDIC Survey of Household Use of Banking and Financial Services.



(a) Across Age



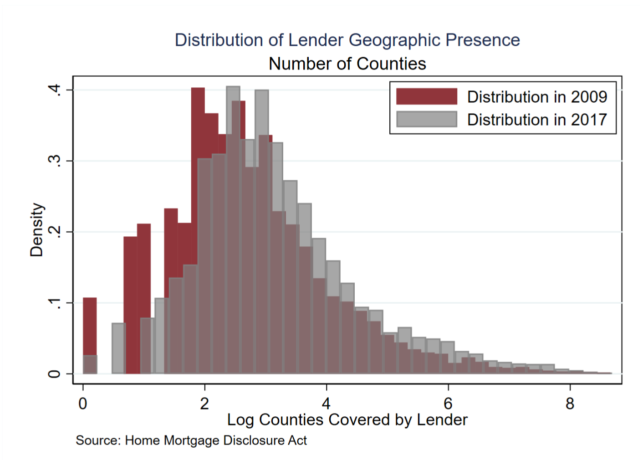
(b) Young



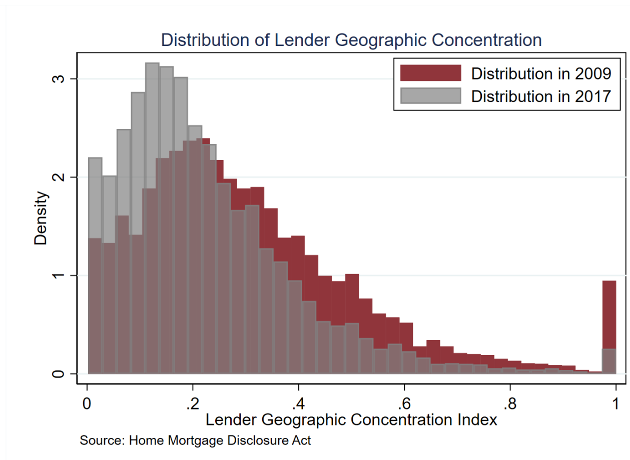
(c) Old

Figure 3: Geographic Expansion and Increased Bank Competition

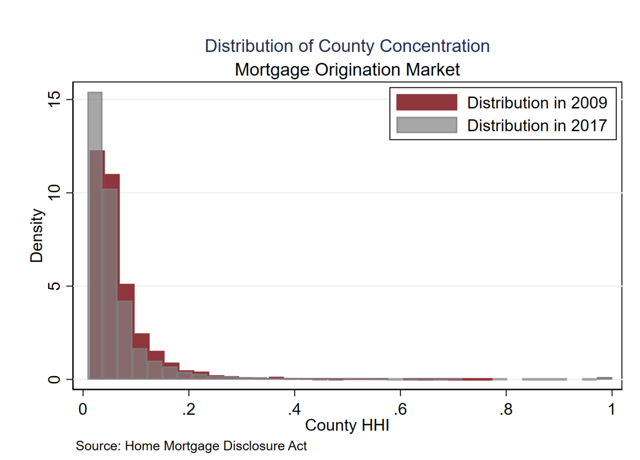
This figure plots the distributions of geographic expansion of lenders in 2009 versus 2017. Panel (a) plots the histogram of log number of counties covered by each mortgage originator in 2009 and in 2017. Panel (b) plots the histogram of the geographic concentration. Geographic concentration of a lender is calculated as the sum of squared share of mortgage origination activity in each county, i.e., $\sum_k \in \mathbb{K}_i \frac{Volume_{ik}}{\sum_k \in \mathbb{K}_i Volume_{ik}}$. Panel (c) and (d) plot the histograms of county HHI index, where (c) is full sample, and (d) focuses on the largest 500 counties in the US. Source: HMDA.



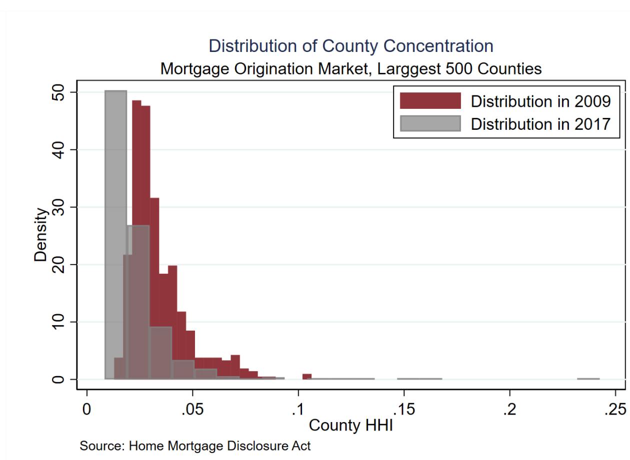
(a) Number of Counties



(b) Lender Geographic Concentration



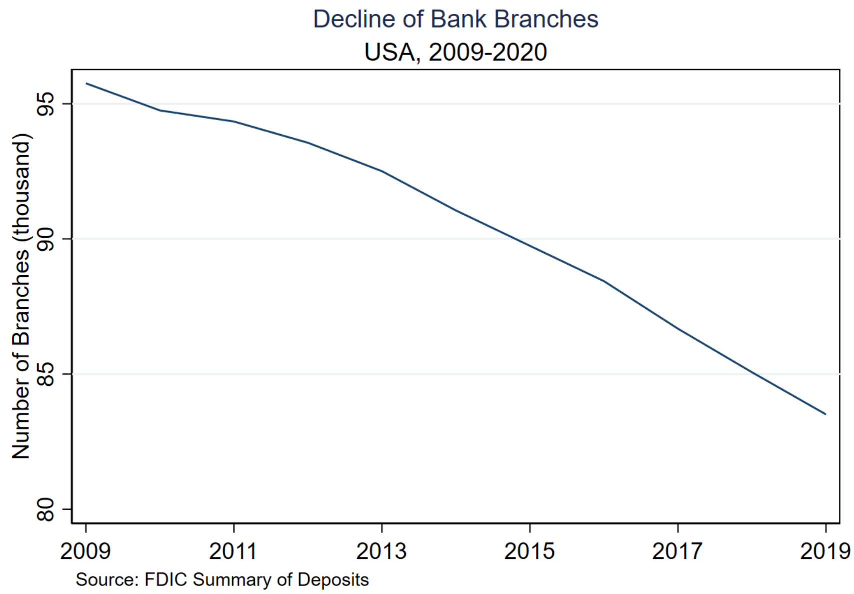
(c) County HHI - Full



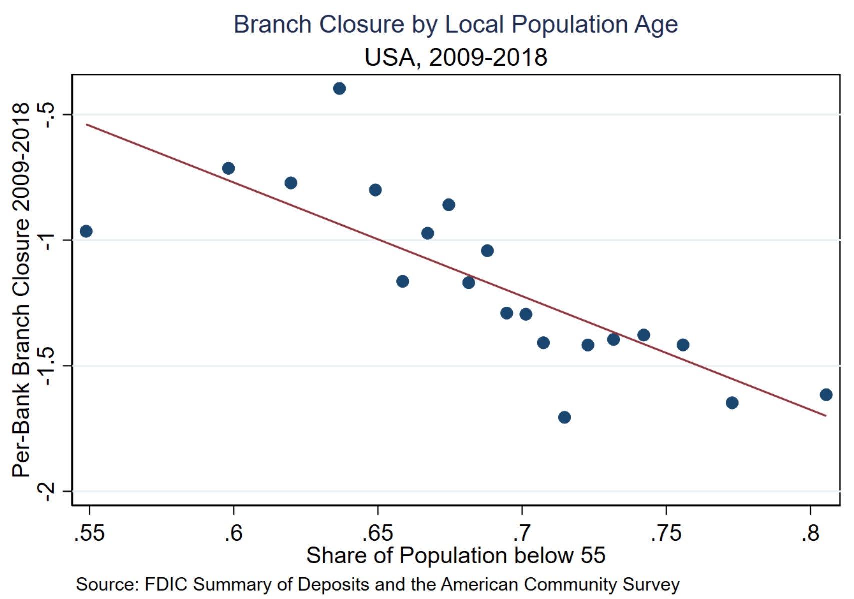
(d) County HHI - Big

Figure 4: Bank Branch Closure

Panel (a) of this figure plots the time series of total number of branches from 2009 to 2020. Panel (b) plots county-level per-bank branch closure rate from 2009 to 2018 against the county share of population below 55. Source: FDIC Summary of Deposits and the American Community Survey.



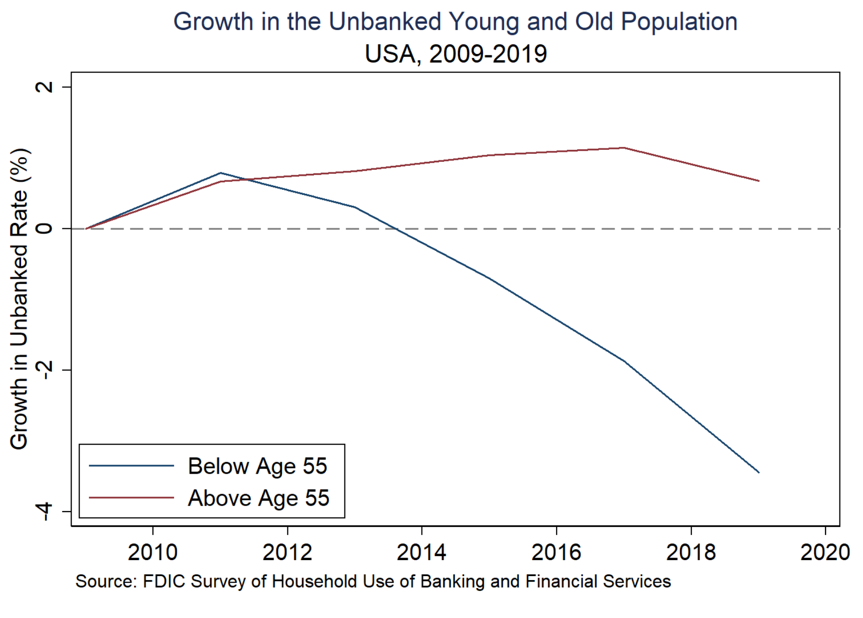
(a) Total



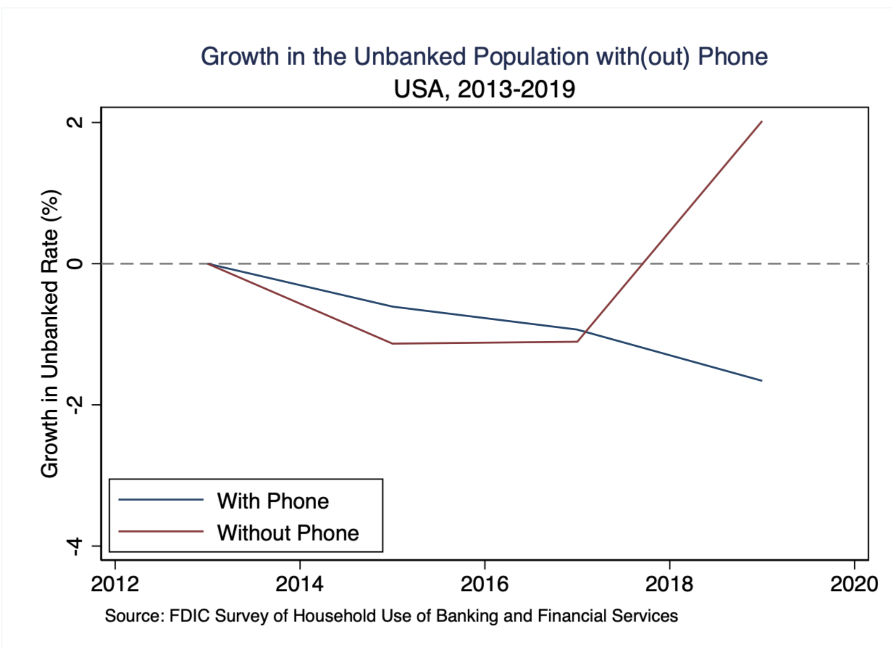
(b) Cross-Section

Figure 5: Growth in the Unbanked Young and Old Population

This figure plots the growth rate of unbanked consumers under 55 versus above 55 over years (Panel (a)) and with versus without phones (Panel (b)). Source: FDIC Survey of Household Use of Banking and Financial Services.



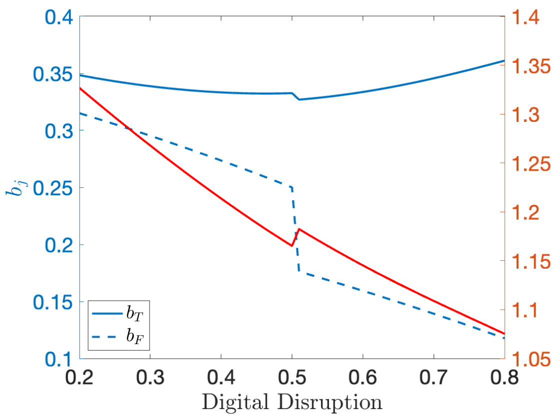
(a) Age



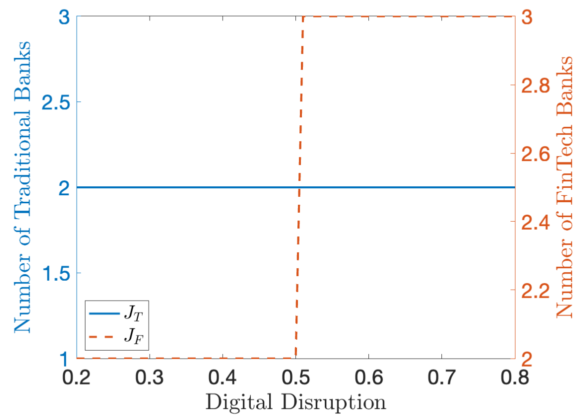
(b) Phone

Figure 6: The Impact of Digital Disruption on Bank Competition

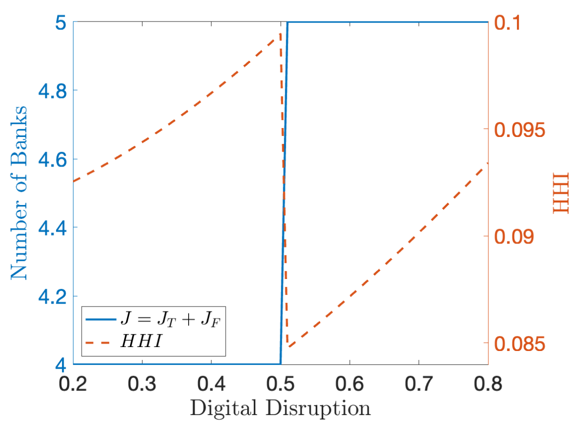
The figures plots numerical results of our model to illustrate the impact of digital disruption on bank competition. The parameters used are $\{\alpha_y, \alpha_o\} = \{2, 0.4\}$, $\{\beta_y, \beta_o\} = \{0.8 - DD, 0.8\}$, $\{\gamma_y, \gamma_o\} = \{1.15 \times DD, 0\}$, $\{\kappa_T, \kappa_F\} = \{0.3, 0.35\}$, $c_T = c_F = 0.1$, $\{d_T, d_F\} = \{0, 1\}$, $\{\lambda_T, \lambda_F\} = \{0.4, 0.35\}$, $FC_T = FC_F = 0.08$. The x-axis is the value of DD, which is the index of digital disruption. As DD increases, β_y decreases and γ_y increases. Panel (a)-(d) plots the equilibrium results when $\mu_0 = \mu_y = 0.5$, and panel (e) compares total branches when $\mu_y = 50\%$ versus $\mu_y = 60\%$.



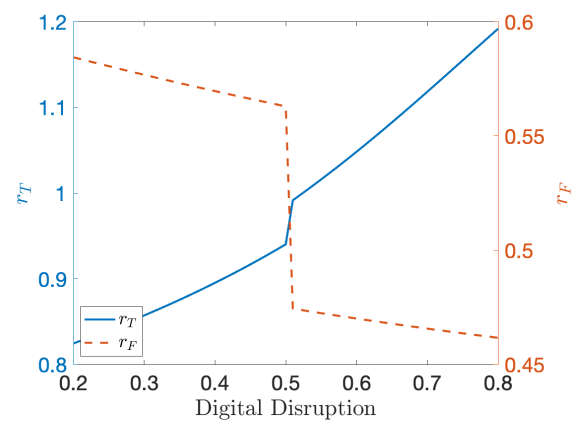
(a) Branch, (b_T **v.s.** b_F)



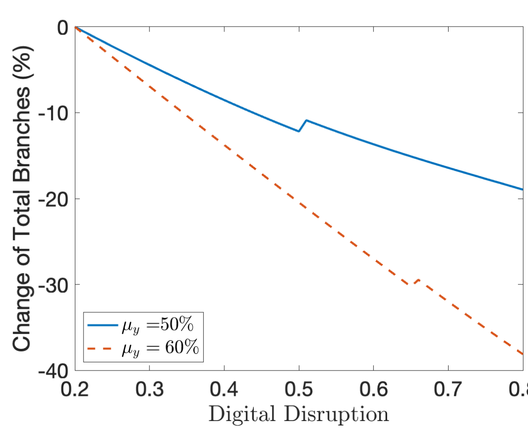
(b) Entry



(c) Competition



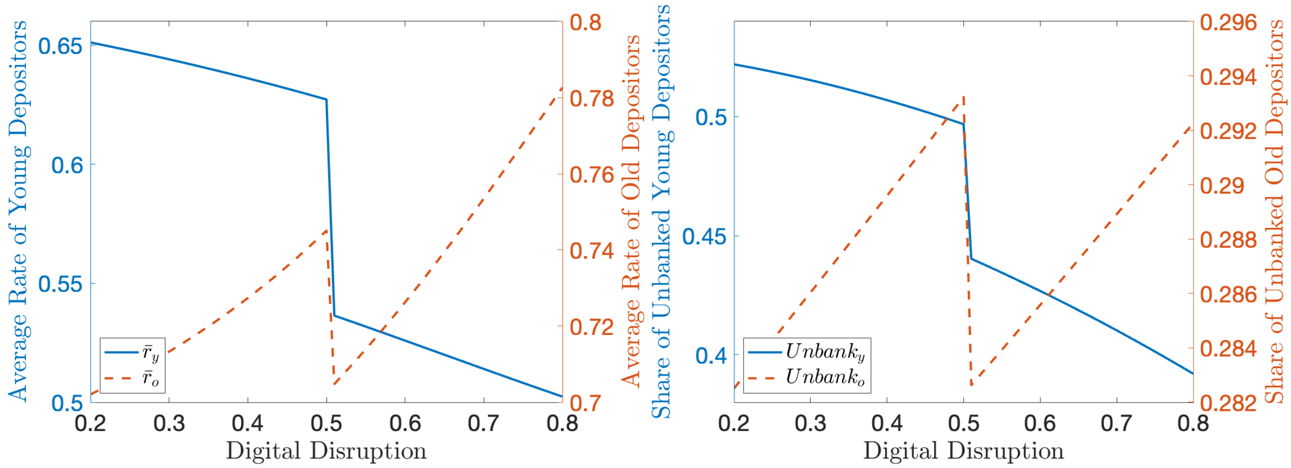
(d) Rate, (r_T **v.s.** r_F)



(e) Total Branch ($\mu_y = 50\%$ **v.s.** $\mu_y = 60\%$)

Figure 7: The Distributional Effects of Digital Disruption

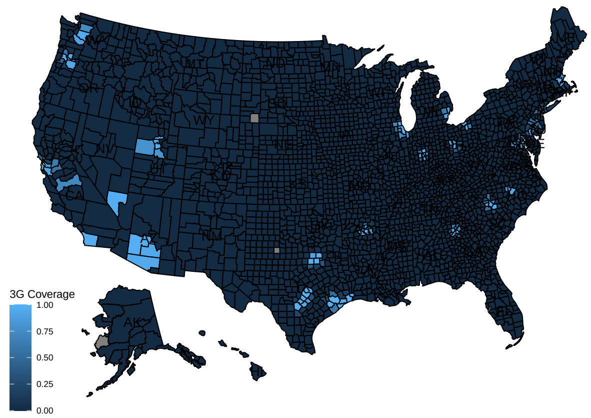
The figures plots numerical results of our model to illustrate the distributional effect of digital disruption. The parameters used are $\mu_0 = \mu_y = 0.5$, $\{\alpha_y, \alpha_o\} = \{2, 0.4\}$, $\{\beta_y, \beta_o\} = \{0.8 - DD, 0.8\}$, $\{\gamma_y, \gamma_o\} = \{1.15 \times DD, 0\}$, $\{\kappa_T, \kappa_F\} = \{0.3, 0.35\}$, $c_T = c_F = 0.1$, $\{d_T, d_F\} = \{0, 1\}$, $\{\lambda_T, \lambda_F\} = \{0.4, 0.35\}$, $FC_T = FC_F = 0.08$. The x-axis is the value of DD, which is the index of digital disruption. As DD increases, β_y decreases and γ_y increases.



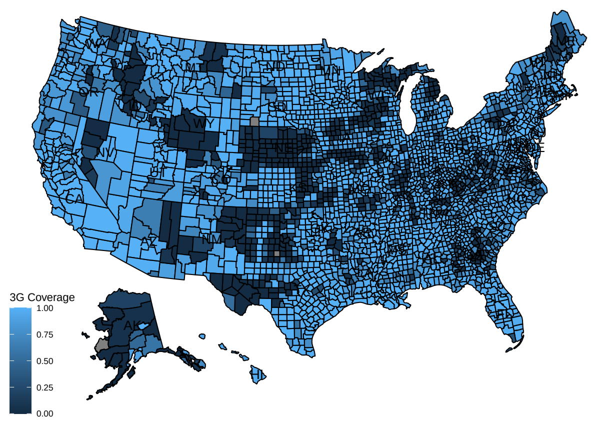
(a) Average Rate (Young v.s. Old) **(b) Unbank (Young v.s. Old)**

Figure 8: Maps of 3G Coverage

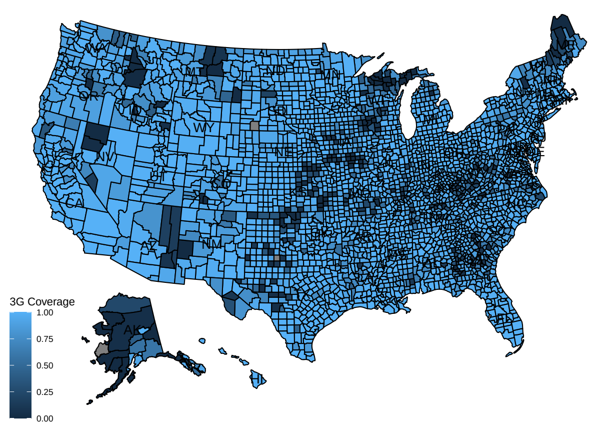
This figure plots 3G coverage at the county level in 2007, 2012, and 2018. 3G coverage is calculated as the average of the value of 3G availability weighted by the population density in each grid cell across all grid-cells in each county's polygon. Source: Collins Bartholomew's Mobile Coverage Explorer



(a) 2007



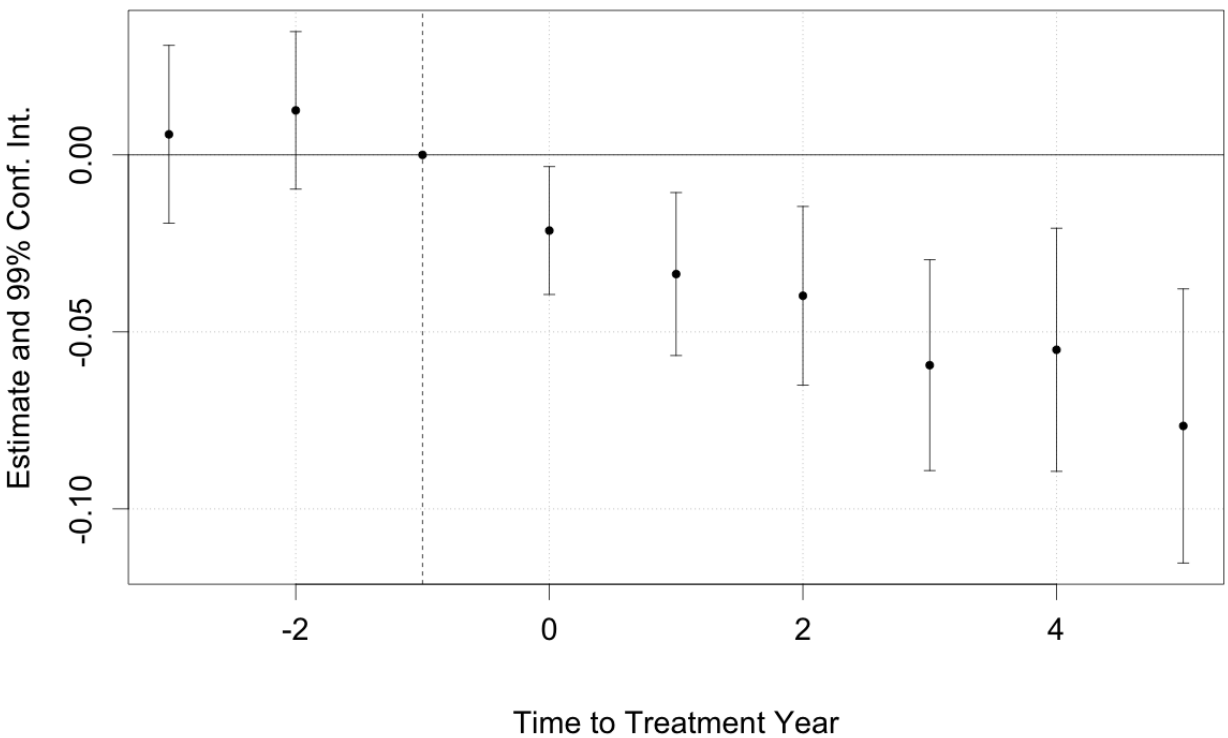
(b) 2012



(c) 2018

Figure 9: Event Study for Bank Closure

This figure plots dynamic DiD results for branch closure at the county-year level. The treatment group includes counties whose 3G coverage increased more than 50% in one year. The control group is constructed using matching methodology, as described by Table 4.



B Tables

Table 1: Summary Statistics

Panels A-B report the summary statistics of bank and county data used. Variables are defined in Section 4.2. Panel C presents the proportion of interviewees belonging to the certain category from the FDIC surveys in 2009, 2011, 2013, 2015, and 2017.

	Count	Mean	St. Dev.	$q_{5\%}$	$q_{25\%}$	Median	$q_{75\%}$	$q_{95\%}$
Panel A: County characteristics								
3G Coverage	34,081	0.593	0.440	0.000	0.000	0.865	0.990	1.000
Per capita income, in \$K	33,586	38.143	11.376	25.346	30.987	36.067	42.645	57.162
GDP, in \$B	33,586	5.419	23.537	0.121	0.356	0.909	2.634	21.598
Population, in K	34,070	101.471	323.015	3.088	11.445	26.265	68.296	433.952
$\frac{\#BranchClosure_{c,t}}{\#Banks_{c,t-1}}$	34,081	0.057	0.116	0.000	0.000	0.000	0.083	0.286
$\frac{\#Branches_{c,t}}{\#Banks_{c,t-1}}$	34,081	2.184	1.622	1.000	1.250	1.667	2.455	5.333
#Lenders	31,226	106.179	101.995	11.000	38.000	74.000	136.000	321.000
HHI (in bps)	31,226	910.684	893.637	269.791	436.381	648.843	1045.187	2395.384
Share^{wBranch}, in %	31,226	47.859	24.590	0.000	31.710	51.876	66.806	82.010
Lightning	3,220	1.701	1.307	0.041	0.616	1.406	2.671	4.222
Panel B: Bank-county characteristics								
	Count	Mean	St. Dev.	$q_{5\%}$	$q_{25\%}$	Median	$q_{75\%}$	$q_{95\%}$
$\#Branch_{b,c,t}$	668,019	2.007	5.522	0.000	0.000	1.000	2.000	7.000
Spread$^{12MCD10K}_{b,t,qt}$, in%	445,830	0.009	0.909	-1.475	-0.475	-0.100	0.535	1.665
Spread$^{36MCD10K}_{b,t,qt}$, in %	407,209	-0.447	1.015	-2.125	-1.065	-0.520	0.220	1.310
Panel C: FDIC Surveys								
	Young	Lower-income	Educated	Phone	BankTeller	MobileBanking	Unbank	Losing Banking Access
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Proportion	0.588	0.416	0.614	0.8984	0.283	0.104	0.074	0.474
Count	203,184	203,184	203,184	105,437	99,876	99,876	203,184	12,931

Table 2: The Impact of 3G Coverage on Bank Closures at Bank-county Level

This table reports how 3G coverage affect banks' decision to close branches using bank-county-year level data. The dependent variable in the first two columns, $\frac{\#BranchClosure_{b,c,t}}{\#Branches_{b,c,t-1}}$, is the ratio of the number of branch closures of bank b in county c at year t and the total number of branches the bank had last year in the same county. The dependent variable in the rest of the columns is the number of branches, in the log scale, of bank b in county c at year t. 3G coverage$_{c,t}$ is the proportion of population with access to 3G networks in county c at year t. "Young County" refers to counties with the median age below 40 years old. Log(PerCapitaIncome)$_{c,t}$, log(CountyGDP)$_{c,t}$, log(TotalPop)$_{c,t}$ are per ca capital income, GDP and population in county c at year t. Standard errors are clustered at the county level. Numbers in parentheses are t-statistics. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	$\frac{\#BranchClosure_{b,c,t}}{\#Branches_{b,c,t-1}}$		$\log(1+\#Branch_{b,c,t})$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full	Full	Full	Full	$med \leq 40$	$med > 40$	Full
3G Coverage	0.004***	0.005***	−0.011***	−0.007**	−0.012**	0.002	−0.002
	(4.283)	(4.451)	(−2.748)	(−2.034)	(−2.576)	(0.337)	(−0.274)
3G Coverage×Young County							−0.018*
							(−1.958)
log(PerCapitaIncome)	0.006	0.002	−0.071***	0.001	−0.017	0.022	−0.086***
	(1.083)	(0.449)	(−3.296)	(0.054)	(−0.610)	(0.974)	(−3.600)
log(CountyGDP)	−0.003	−0.003	−0.010	−0.006	0.001	−0.014	−0.011
	(−1.010)	(−1.154)	(−1.020)	(−0.740)	(0.060)	(−1.336)	(−0.977)
log(TotalPop)	−0.019***	−0.017**	0.538***	0.422***	0.395***	0.305***	0.535***
	(−2.798)	(−2.295)	(13.990)	(14.459)	(9.102)	(5.881)	(11.181)
Bank×County FE	✓	✓	✓	✓	✓	✓	✓
Bank×Year FE	✓		✓				
Bank×State×Year FE		✓		✓	✓	✓	✓
Observations	476,376	476,376	476,376	476,376	280,685	195,691	476,376
Adjusted R^2	−0.047	0.048	0.850	0.887	0.893	0.896	0.854

Table 3: The Impact of 3G Coverage on Bank Closure at County Level

This table reports how 3G coverage affect aggregate branch closures at the county-year level. The dependent variable in the first two columns, $\frac{\#BranchClosure_{c,t}}{\#Branches_{c,t-1}}$, is the ratio of the number of branch closures in county c at year t and the total number of branches in the same county at year $t-1$. The dependent variable in the rest of the columns is the number of branches, in the log scale, in county c at year t. 3G coverage$_{c,t}$ is the proportion of population with access to 3G networks in county c at year t. "med ≤ 40" (resp. "med > 40") indicates the median age in a county is below (resp. above) 40 years old. Log(PerCapitaIncome)$_{c,t}$, log(CountyGDP)$_{c,t}$, log(TotalPop)$_{c,t}$ are per ca capital income, GDP and population in county c at year t. Standard errors are clustered at the county level. Numbers in parentheses are t-statistics. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	$\frac{\#BranchClosure_{c,t}}{\#Banks_{c,t-1}}$		$\frac{\#Branches_{c,t}}{\#Banks_{c,t-1}}$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full	Full	Full	Full	$med \leq 40$	$med > 40$	Full
3G Coverage	0.007***	0.008***	−0.083***	−0.087***	−0.110***	−0.047***	−0.047***
	(2.704)	(2.898)	(−7.404)	(−7.398)	(−5.730)	(−3.890)	(−3.687)
3G Coverage×Young County							−0.061***
							(−4.579)
log(PerCapitaIncome)	−0.021**	−0.023**	0.157***	0.060*	0.078	0.028	0.048
	(−2.140)	(−2.145)	(5.010)	(1.694)	(1.149)	(0.772)	(1.378)
log(CountyGDP)	−0.004	−0.001	0.006	0.017	0.034	0.009	0.017
	(−0.861)	(−0.330)	(0.440)	(1.244)	(1.504)	(0.553)	(1.222)
log(TotalPop)	−0.032	−0.050**	−0.020	−0.088	−0.011	−0.042	−0.002
	(−1.402)	(−1.966)	(−0.210)	(−0.932)	(−0.073)	(−0.328)	(−0.024)
County FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓		✓				
State×Year FE		✓		✓	✓	✓	✓
Observations	33,575	33,575	33,575	33,575	14,478	19,097	33,575
Adjusted R^2	0.278	0.301	0.980	0.981	0.982	0.981	0.982

Table 4: Event Study for Bank Closure

The table reports DiD analysis results for county-level branch closures. The dependent variables are the same as those in Table 3. The treatment group includes counties that had a sharp increase in 3G coverage, more than 50% in a single year. For each treated county, we construct a control county if a county has the closest matching score based on county characteristics but did not experience a sharp increase in 3G coverage ever nor reach 30% 3G coverage three years after the treatment year. The sample covers a two-year window around the shock year, [-2, -1, 0, 1, 2]. Post equals to 1 if the window is above 0 and zero otherwise. Standard errors are clustered at the county level. Numbers in parentheses are t-statistics. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	$\frac{\#BranchClosure_{c,t}}{\#Banks_{c,t-1}}$		$\frac{\#Branches_{c,t}}{\#Banks_{c,t-1}}$	
	(1)	(2)	(3)	(4)
Treat×Post	0.017***	0.017***	−0.056***	−0.053***
	(5.529)	(5.307)	(−7.427)	(−7.006)
log(PerCapitaIncome)		−0.028		0.128***
		(−1.473)		(4.071)
log(countyGDP)		−0.019*		0.015
		(−1.878)		(0.876)
log(TotalPop)		0.028		−0.205
		(0.378)		(−1.267)
Cohort×County FE	✓	✓	✓	✓
Cohort×Year FE	✓	✓	✓	✓
Observations	14,357	14,237	14,357	14,237
Adjusted R^2	0.182	0.183	0.986	0.986

Table 5: Lightening, 3G Coverage, and Bank Closure

The table reports an IV analysis, where the expansion of 3G coverage is instrumented using lightening strikes at the county level. High lightening strikes represent counties where the proportion of population affected by lightening is higher than the sample median in one year. Column (1) presents the results of the first stage of IV regression, while the rest of columns are results for the second stage. Standard errors are clustered at the county level. Numbers in parentheses are t-statistics. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	First stage	Bank County Level		County Level			
	3G Coverage	$\frac{\#BranchClosure_{b,c,t}}{\#Branches_{b,c,t-1}}$	$\log(1+\#Branches)_{b,c,t}$	$\frac{\#BranchClosure_{c,t}}{\#Banks_{c,t-1}}$	$\frac{\#Branches_{c,t}}{\#Banks_{c,t-1}}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full	Full	Full	Full	Full	$med \leq 40$	$med > 40$
$\mathbb{1}$(High Lightning) $\times$ $Year$	−0.0109***						
	(−4.950)						
$\widehat{\text{3G Coverage}}$		0.0861*	−0.296***	0.100*	−0.549***	−1.269**	−0.294***
		(1.696)	(−2.616)	(1.939)	(−4.362)	(-2.490)	(-3.214)
log(PerCapitaIncome)	−0.255***	0.00997	−0.0249	−917	−0.0397	−0.173	−0.0122
	(−6.420)	(1.369)	(−1.539)	(−0.055)	(−0.976)	(-1.308)	(-0.369)
log(CountyGDP)	0.0663***	−0.00482*	−0.00239	−0.00769	0.0429***	0.112**	0.0214
	(3.704)	(−1.728)	(−0.385)	(−1.290)	(2.958)	(2.448)	(1.529)
log(TotalPop)	0.139**	0.00663	0.325***	−0.0685***	−0.305***	−0.841***	0.0171
	(2.185)	(0.452)	(9.959)	(−3.346)	(−6.123)	(-3.796)	(0.205)
3G $\text{Coverage}_{2007}\times$ Year	−0.0816***	0.00591	−0.0192**	0.00874**	0.0152	−0.0365	0.0351***
	(−50.320)	(1.503)	(−2.200)	(2.023)	(1.445)	(-0.921)	(4.014)
County FE	✓			✓	✓	✓	✓
Bank×County FE		✓	✓				
State×Year FE	✓			✓	✓	✓	✓
Bank×State×Year FE		✓	✓				
Observations	33,575	420,584	434,181	33,575	33,575	14,351	19,056

Table 6: Effect of 3G Coverage on Banks' Branching Decisions in the Lending Market

This table reports how 3G coverage affects the branching decisions of banks in the lending market. The analysis unit is bank-county-year level. Columns (1)-(2) include both incumbent and new entry banks (which did not originate any loans in previous year) for a given county. Columns (3)-(4) include new entry banks only. The dependent variable is the dependent variable in other columns is the natural logarithm of 1 plus the number of branches. Columns (2)(4) report the using lighting strikes frequency as an instrument to 3G coverage. All columns include State-Bank-Year fixed effects. In addition, columns (1)-(2) include Bank-County fixed effects. Standard errors are clustered at the county level. Numbers in parentheses are t-statistics. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	log(1+#Branches)			
	All Banks		Entry	
	(1)	(2)	(3)	(4)
3G Coverage	-0.020***		-0.005***	
	(-8.411)		(-2.828)	
$\widehat{\text{3G Coverage}}$		-0.103**		-0.003*
		(-2.404)		(-1.735)
log(PerCapitaIncome)	-0.056***	-0.067***	-0.035***	-0.033***
	(-5.090)	(-7.338)	(-10.527)	(-10.082)
log(CountyGDP)	0.005	0.005*	0.013***	0.013***
	(1.213)	(1.904)	(10.144)	(10.066)
log(TotalPop)	0.393***	0.337***	0.018***	0.017***
	(12.714)	(27.360)	(5.722)	(5.419)
Lender HomePurchase	0.006***	0.006***	0.020***	0.020***
	(38.991)	(57.448)	(46.003)	(46.016)
Lender Refinancing	0.007***	0.007***	0.022***	0.022***
	(41.461)	(60.671)	(48.310)	(48.318)
3G $\text{Coverage}_{2007}\times$ Year		0.001		-0.002***
		(0.180)		(-4.002)
Bank×County FE	✓	✓		
State×Bank×Year FE	✓	✓	✓	✓
Observations	981,232	980,331	207,665	207,354
Adjusted R^2	0.947		0.266	

Table 7: The Impact of 3G Coverage on Lending Competition

This table reports the effect of 3G coverage on lending competition in the lending market. The dependent variable is HHI in the odd columns and the number of lenders in the even columns. Both HHI and the number of lenders are constructed using all lenders. Columns (1)-(4) include all loans. All columns include county and year fixed effects. Standard errors are clustered at the county level. Numbers in parentheses are t-statistics. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	All Loans			
	(1)	(2)	(3)	(4)
	HHI	log(#Lenders)	HHI	log(#Lenders)
3G Coverage	-37.850***	0.038***		
	(-2.601)	(8.625)		
$3G\ \widehat{Coverage}$			-39.493**	0.037***
			(-2.576)	(7.946)
log(PerCapitaIncome)	46.553	-0.049*	3.928	-0.045*
	(0.521)	(-1.835)	(0.044)	(-1.664)
log(countyGDP)	-2.066	0.001	2.797	0.001
	(-0.060)	(0.113)	(0.080)	(0.113)
log(TotalPop)	-1197.331***	0.517***	-1193.846***	0.535***
	(-8.240)	(12.060)	(-7.863)	(11.866)
log(TotalLoan)	344.857***	0.279***	391.739***	0.272***
	(9.307)	(31.218)	(10.344)	(29.806)
3G $Coverage_{2007} \times$ Year			-2.982	-0.002
			(-1.032)	(-1.331)
County FE	✓	✓	✓	✓
State×Year FE	✓	✓	✓	✓
Observations	30501	30,501	30,292	30,292
Adjusted R^2	0.776	0.987		

Table 8: Effect of 3G on Deposit Pricing

This table reports the impact of 3G on deposit pricing for banks with branches. The dependent variable is the deposit spread. All columns include bank, county and year-quarter fixed effects. Columns (2) and (5) further include bank×county fixed effects. We use instrumented 3G coverage by lightening strikes as independent variables in columns (3) and (6). Standard errors are clustered at the county level. Numbers in parentheses are t-statistics. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	$Spread^{12MCD10K}$			$Spread^{36MCD10K}$		
	(1)	(2)	(3)	(4)	(5)	(6)
3G Coverage	0.019**	0.018**		0.013*	0.012	
	(2.316)	(2.110)		(1.688)	(1.512)	
3G $\widehat{\text{Coverage}}$			0.196***			0.228***
			(4.090)			(4.115)
log(PerCapitaIncome)	−0.126***	−0.120***	-0.0832***	−0.131***	−0.127***	-0.103***
	(−2.937)	(−2.728)	(-6.108)	(−3.048)	(−2.865)	(-6.599)
log(countyGDP)	0.019	0.020	0.0218***	0.028	0.029	0.0362***
	(0.974)	(1.031)	(3.256)	(1.364)	(1.421)	(4.707)
log(#Banks)	−0.013	−0.012	-0.0640***	−0.013	−0.013	-0.0639***
	(−0.566)	(−0.492)	(-6.760)	(−0.560)	(−0.511)	(-6.213)
log(TotalPop)	0.203***	0.223***	0.328***	0.162**	0.186**	0.404***
	(2.701)	(2.783)	(7.696)	(2.178)	(2.334)	(8.130)
Bank FE	✓			✓		
County FE	✓			✓		
Bank×County FE		✓	✓		✓	✓
State×Quarter FE	✓	✓	✓	✓	✓	✓
Observations	332,708	332,708	312,417	304,922	304,922	286,625
Adjusted R^2	0.907	0.909		0.921	0.924	

Table 9: Effect of 3G on Loan Pricing

This table reports the impact of 3G coverage on loan pricing. The underlying sample includes loan-level observations of all bank originated loans recorded in HMDA in 2018. The outcome variable in Panel A is origination fee. The outcome variable in Panel B is mortgage interest rate. In both panels, $Branch$ equals 100 if the lender has a branch in the county and 0 otherwise. $log(1 + \#Branches)$ is the logarithm of one plus the number of branches a bank has for a given county. The Unreported $Controls$ include the natural logarithm of loan size, loan type, loan purpose (home purchases, refinancing or others), loan-to-value ratios, debt-to-income ratios, and borrowers' income in natural logarithm, gender, age, and race. Standard errors are clustered at the county level. Numbers in parentheses are t-statistics. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	Panel A: Origination Fees (%)			
	(1)	(2)	(3)	(4)
Branch×3G Coverage	0.126*	0.089		
	(1.85)	(1.46)		
log(1+#Branches)×3G Coverage			0.322***	0.315***
			(5.39)	(5.33)
log(1+#Branches)			-0.403***	-0.400***
			(-6.84)	(-6.85)
Branch	-0.378***	-0.318***		
	(-5.75)	(-5.39)		
3G Coverage	-0.729***		-0.797***	
	(-15.58)		(-16.28)	
Controls	✓	✓	✓	✓
State FE	✓		✓	
County FE		✓		✓
Bank FE	✓	✓	✓	✓
Observations	1,815,347	1,815,322	1,815,347	1,815,322
Adjusted R^2	0.211	0.214	0.211	0.214

	Panel B: Interest Rate (%)			
	(1)	(2)	(3)	(4)
Branch×3G Coverage	-0.049	-0.056*		
	(-1.62)	(-1.92)		
log(1+#Branches)×3G Coverage			-0.033	-0.064**
			(-1.41)	(-2.13)
log(1+#Branches)			0.027	0.058**
			(1.16)	(2.02)
Branch	0.044	0.056**		
	(1.47)	(2.01)		
3G Coverage	0.025		0.025	
	(0.94)		(1.08)	
Controls	✓	✓	✓	✓
State FE	✓		✓	
County FE		✓		✓
Bank FE	✓	✓	✓	✓
Observations	1,809,045	1,809,020	1,809,045	1,809,020
Adjusted R^2	0.677	0.677	0.677	0.677

Table 10: Impact of 3G Coverage on Consumers' Access to Banking Services

The table presents results of the impact of 3G coverage on consumers' access to banking services using branches versus mobile banking, using FDIC Survey of Consumers Use of Banking and Financial Services. The dependent variable is the log ratio of the number of consumers using mobile banking to bank tellers . "Young" refers to consumers under 45 years old. Numbers in parentheses are t-statistics. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	$log(\frac{1+MobileBanking}{1+Branches})$		
	(1)	(2)	(3)
Young	5.315***	−1.444	−1.426
	(19.551)	(−1.215)	(−1.184)
3G Coverage		−6.248***	
		(−5.415)	
3G Coverage×Young		7.431***	7.408***
		(5.841)	(5.742)
MSA FE	✓	✓	
Year FE	✓	✓	
MSA×Year FE			✓
Observations	2,594	2,594	2,594
Adjusted R^2	00.256	0.310	0.319

Table 11: Preference for Branches by Borrowers' Age

This table reports the effect of 3G coverage on borrowers' choices of lenders with branches by borrowers' age using loan-level data from HMDA in 2018. The outcome variable equals 100 if the lender has a branch in the county and 0 otherwise. The independent variables of interest are the indicator variables for the borrowers' age range. For example, *34<Borrower Age<45* equals one if the borrower is between 34 and 45 years old. The Unreported *Controls* include the natural logarithm of loan size, loan type, loan purpose (home purchases, refinancing or others), loan-to-value ratios, debt-to-income ratios, and borrowers' income in natural logarithm, gender, and race. The underlying sample includes loan-level observations of all originated loans recorded in HMDA in 2018. Standard errors are clustered at the county level. Numbers in parentheses are t-statistics. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	Likelihood of choosing a lender with a branch			
	(1)	(2)	(3)	(4)
34<Borrower Age<45	-0.105	-0.213***	-6.963***	-2.717***
	(-1.24)	(-6.52)	(-8.99)	(-5.49)
44<Borrower Age<55	1.741***	-0.032	-9.125***	-4.214***
	(15.08)	(-0.75)	(-9.58)	(-7.18)
54<Borrower Age<65	4.916***	0.345***	-7.223***	-5.436***
	(30.08)	(6.01)	(-7.35)	(-9.06)
Borrower Age>64	10.957***	1.172***	-5.361***	-5.049***
	(46.18)	(14.13)	(-4.33)	(-7.24)
34<Borrower Age<45×3G Coverage			6.968***	2.545***
			(8.80)	(5.08)
44<Borrower Age<55×3G Coverage			11.036***	4.248***
			(11.24)	(7.14)
54<Borrower Age<65×3G Coverage			12.338***	5.877***
			(11.70)	(9.62)
64<Borrower Age×3G Coverage			16.600***	6.328***
			(12.43)	(8.84)
Controls	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Lender FE		✓		✓
Observations	6,125,807	6,125,767	6,125,807	6,125,767
Adjusted R^2	0.149	0.780	0.149	0.780

Table 12: Distributional Effect of 3G on Loan Pricing across Age Groups

This table reports the interaction effect between 3G coverage and borrower age on loan pricing. The underlying sample includes all loans originated by banks in 2018 from HMDA. The analysis unit is at the loan level. The dependent variable is the loan origination fees in columns (1)-(2), and the loan interest rates in columns (3)-(4). The key independent variables of interest are the interaction term between 3G coverage and indicator variables for borrowers' age range. The Unreported *Controls* include the natural logarithm of loan size, loan type, loan purpose (home purchases, refinancing or others), loan-to-value ratios, debt-to-income ratios, and borrowers' income in natural logarithm, gender, age, and race. All columns include bank fixed effects. Odd columns include state fixed effects, and even columns include county fixed effects. Standard errors are clustered at the county level. Numbers in parentheses are t-statistics. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	Origination Fees (%)		Interest Rate (%)	
	(1)	(2)	(3)	(4)
3G Coverage	-1.071***		-0.0615**	
	(-14.20)		(-2.12)	
34<Borrower Age<55×3G Coverage	0.213***	0.215***	0.0798***	0.0588**
	(3.57)	(3.67)	(2.94)	(2.28)
Borrower Age>54×3G Coverage	0.543***	0.502***	0.0636*	0.0287
	(6.80)	(6.16)	(1.80)	(0.83)
34<Borrower Age<55	-0.170***	-0.182***	-0.0691**	-0.0494*
	(-3.01)	(-3.26)	(-2.56)	(-1.92)
Borrower Age>54	-0.619***	-0.595***	-0.126***	-0.0924***
	(-8.30)	(-7.82)	(-3.87)	(-2.93)
Controls	✓	✓	✓	✓
State FE	✓		✓	
County FE		✓		✓
Bank FE	✓	✓	✓	✓
Observations	1,815,347	1,815,322	1,809,045	1,809,020
Adjusted R^2	0.210	0.214	0.677	0.677

Table 13: Digital Inequality

The table presents results of the impact of 3G coverage on consumers' access to banking services, using FDIC Survey of Consumers Use of Banking and Financial Services. "Unbank" refers to consumers who do not have a bank account, and "Losing Banking Access" refers to consumers who once had a bank account but turn unbanked. "Young" refers to consumers under 45 years old; "Lower-income" refers to consumers with less than \$50,000 annual income; "Education" refers to consumers with college education; "Phone" refers to consumers with a mobile phone. The observations are weighted to account for non-response and under-coverage. Numbers in parentheses are t-statistics. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	Unbank								Losing Banking Access	
	Young		Lower-income		Educated		Phone		Young	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
3G Coverage	0.019**		−0.006		0.039***		0.513***		0.019***	
	(2.104)		(−0.741)		(3.889)		(3.817)		(2.985)	
Young	0.075***	0.073***							0.056***	0.056***
	(6.639)	(6.391)							(7.200)	(7.130)
3G Coverage×Young	−0.029**	−0.027**							−0.039***	−0.039***
	(−2.467)	(−2.290)							(−4.794)	(−4.771)
Lower-income			0.034	−0.014						
			(1.064)	(−0.361)						
3G Coverage×Lower-income			0.094***	0.144***						
			(2.876)	(3.622)						
Education					−0.063***	−0.063***				
					(−5.754)	(−5.641)				
3G Coverage×Education					−0.054***	−0.054***				
					(−4.750)	(−4.675)				
Phone							0.231**	0.217**		
							(2.278)	(2.124)		
3G Coverage×Phone							−0.340***	−0.326***		
							(−3.298)	(−3.137)		
MSA	✓		✓		✓		✓		✓	
Year FE	✓		✓		✓		✓		✓	
MSA×Year FE		✓		✓		✓		✓		✓
Observations	144,794	144,794	144,794	144,794	144,794	144,794	75,337	75,337	144,794	144,794
Adjusted R^2	0.022	0.024	0.061	0.064	0.057	0.060	0.031	0.033	0.009	0.012

C Model Analysis

C.1 The General Case

Due to the nested structure, the likelihood $s_{i,}$ can be decomposed into two parts, 1) the likelihood that one-type is chosen, and 2) conditional on that, bank j is selected. Following formula based on the property of the generalized extreme value distribution, the conditional probability 2) is given by

$$Pr(j|j \in t) = \frac{A_{i,j}}{Z_{i,t}}, \quad t \in \{T, F\},$$

where

$$A_{i,j} = \exp(\frac{1}{\lambda_t}(-\alpha_i r_j + \beta_i b_j + \gamma_i d_j)), \qquad Z_{i,t} = \sum_{j=1}^{J_t} \exp(\frac{1}{\lambda_t}(-\alpha_i r_j + \beta_i b_j + \gamma_i d_j)).$$

The term $A_{i,j}$ captures the consumer type i's exponential utility from accessing the bank j's service, and the them $Z_{i,t}$ is the sum of her exponential utility assuming she have access to all $t-$type banks. Since we assume all banks in each type are the same, this conditional probability equals to $\frac{1}{J_t}$. The marginal probability that $t-$type bank is chosen is

$$Pr(j \in t) = \frac{Z_{i,j}^{\lambda_t}}{1 + \sum_{t \in \{T,F\}} Z_{i,t}^{\lambda_t}},$$

where we standardize the utility from the outside option to be 1. Intuitively, if $t-$type bank' service generates a higher utility, consumer i is more likely to choose that type of bank. These two terms pin down $s_{i,j}$ where bank j is one of type-t banks as

$$s_{i,j} = \frac{A_{i,j}}{Z_{i,t}} \frac{Z_{i,t}^{\lambda_t}}{1 + \sum_{t \in \{T,F\}} Z_{i,t}^{\lambda_t}}. \tag{19}$$

The first-order condition for banks' optimization problem gives rise to the following equations:

$$FOC_{r_j} : \; r_j = c_j + \frac{\sum_{i \in y,o} \mu_i s_{i,j}}{\sum_{i \in y,o} \mu_i \frac{\alpha_i}{\lambda_t} s_{i,j} \Big(1 + (\lambda_t - 1)\frac{A_{i,j}}{Z_{i,t}} - \lambda_t s_{i,j}\Big)};$$

$$FOC_{b_j} : \; b_j = \frac{1}{\kappa_j}(r_j - c_j) \sum_{i \in y,o} \mu_i \frac{\beta_i}{\lambda_t} s_{i,j} \Big(1 + (\lambda_t - 1)\frac{A_{i,j}}{Z_{i,t}} - \lambda_t s_{i,j}\Big).$$

The difference of $r_j - c_j$ captures the markup of bank j.

Proof. We first derive this derivative $\frac{\partial s_{i,j}}{\partial r_J}$.

$$\begin{aligned}\frac{\partial \ln s_{i,j}}{\partial r_j} = \frac{1}{s_{i,j}}\frac{\partial s_{i,j}}{\partial r_j} &= \frac{\partial \ln A_{i,j}}{\partial r_j} + (\lambda_t - 1)\frac{\partial \ln Z_{i,t}}{\partial r_j} - \frac{\partial \ln(1 + \sum_{t\in\{T,F\}} Z_{i,t}^{\lambda_t})}{\partial r_j} \\ &= \frac{1}{A_{i,j}}\Big(-\frac{\alpha_i}{\lambda_t}\Big)A_{i,j} + (\lambda_t - 1)\frac{1}{Z_{i,t}}\Big(-\frac{\alpha_i}{\lambda_t}\Big)A_{i,j} - \lambda_t\frac{Z_{i,t}^{\lambda_t-1}\Big(-\frac{\alpha_i}{\lambda_t}\Big)A_{i,j}}{1+\sum_{t\in\{T,F\}} Z_{i,t}^{\lambda_t}} \\ &= \Big(-\frac{\alpha_i}{\lambda_t}\Big)\Big(1 + (\lambda_t - 1)\frac{A_{i,j}}{Z_{i,t}} - \lambda_t s_{i,j}\Big) \\ \Longrightarrow \frac{\partial s_{i,j}}{\partial r_j} &= \Big(-\frac{\alpha_i}{\lambda_t}\Big)s_{i,j}\Big(1 + (\lambda_t - 1)\frac{A_{i,j}}{Z_{i,t}} - \lambda_t s_{i,j}\Big).\end{aligned}$$

Similarly, we have

$$\frac{\partial s_{i,j}}{\partial b_j} = \Big(\frac{\beta_i}{\lambda_t}\Big)s_{i,j}\Big(1 + (\lambda_t - 1)\frac{A_{i,j}}{Z_{i,t}} - \lambda_t s_{i,j}\Big).$$

Then, it is straightforward to derive the the first-order conditions for banks:

$$\begin{aligned}r_j &= c_j + D_j\Big(-\frac{\partial D_j}{\partial r_j}\Big)^{-1} = c_j + D_j\Big(-\sum_{i\in\{y,o\}}\mu_i\frac{\partial s_{i,j}}{\partial r_j}\Big)^{-1}, \\ b_j &= \frac{1}{\kappa_j}(r_j - c_j)\frac{\partial D_j}{\partial b_j} = \frac{1}{\kappa_j}(r_j - c_j)\sum_{i\in\{y,o\}}\mu_i\frac{\partial s_{i,j}}{\partial b_j}.\end{aligned}$$

□

C.2 A Simplified Case

The model has a simple closed-form solution when both banks and consumers are homogeneous, which is when $\lambda_t = 1$, $\alpha_i = \alpha$, $\beta_i = \beta$, $\gamma_i = 0$, $c_j = c$, and $\kappa_j = \kappa$. In this case, the market share of each bank j (denoted as s_j) among the total J banks is the same, and it is easy to show that Equations (8) and (9) collapse to be

$$\begin{aligned}r_j &= c + \frac{\sum_{i\in y,o}\mu_i s_{i,j}}{\sum_{i\in y,o}\mu_i\alpha_i s_{i,j}\Big(1 - s_{i,j}\Big)} = c + \frac{s_j}{\alpha s_j(1 - s_j)} = c + \frac{1}{\alpha(1 - s_j)} \\ b_j &= \frac{1}{\kappa_j}\frac{\sum_{i\in y,o}\mu_i s_{i,j}\sum_{i\in y,o}\mu_i\beta_i s_{i,j}\Big(1 - s_{i,j}\Big)}{\sum_{i\in y,o}\mu_i\alpha_i s_{i,j}\Big(1 - s_{i,j}\Big)} = \frac{1}{\kappa}\frac{s_j \times \beta s_j(1 - s_j)}{\alpha s_j(1 - s_j)} = \frac{1}{\kappa}\frac{\beta}{\alpha}s_j,\end{aligned}$$

where $s_j = \frac{exp(-\alpha r_j + \beta b_j)}{1 + J exp(-\alpha r_j + \beta b_j)}$.

Relationship between r_j and b_j We can rewrite the relationship between r_j and b_j as

$$b_j = \frac{\beta(\alpha(r_j - c) - 1)}{\alpha^2\kappa(r_j - c)}$$

Then it is easy to show that $\frac{\partial b_j}{\partial r_j} = \frac{\beta}{(c-r)^2\alpha^2\kappa} > 0$. This is intuitive: to cover the cost to operate more branches, banks have to charge a higher service fee.

Derivative of r_j and b_j in respect with β We take implicit differentiation of β for both r_j and b_j, we get

$$\alpha\kappa\frac{\partial b_j}{\partial \beta} = s_j + \beta\frac{\partial s_j}{\partial \beta}$$
$$\frac{\partial r}{\partial \beta}(1 - s_j) = (r_j - c)\frac{\partial s_j}{\partial \beta}$$
$$\frac{\partial s_j}{\partial \beta} = s_j\frac{-\alpha\frac{\partial r_j}{\partial \beta} + \beta\frac{\partial b_j}{\partial \beta} + b_j}{1 + Jexp(-\alpha r_j + \beta b_j)}$$

Combine above equations, we get

$$\frac{\partial r}{\partial \beta}(1 - s_j) = (r_j - c)s_j\frac{-\alpha\frac{\partial r_j}{\partial \beta} + \beta\frac{\partial b_j}{\partial \beta} + b_j}{1 + Jexp(-\alpha r_j + \beta b_j)}$$
$$\Longrightarrow \frac{\partial r}{\partial \beta}\frac{(1 - s_j)}{(r_j - c)s_j} = \frac{-\alpha\frac{\partial r_j}{\partial \beta} + \beta\frac{1}{\alpha\kappa}\left(\frac{\partial r}{\partial \beta}\frac{\beta(1-s_j)}{r_j - c} + s_j\right) + b_j}{1 + Jexp(-\alpha r_j + \beta b_j)}$$
$$\Longrightarrow \left(\frac{(1 - s_j)}{(r_j - c)s_j} - \frac{-\alpha + \beta\frac{1}{\alpha\kappa}\frac{\beta(1-s_j)}{r_j - c}}{1 + Jexp(-\alpha r_j + \beta b_j)}\right)\frac{\partial r_j}{\partial \beta} = \frac{\beta\frac{1}{\alpha\kappa}s_j + b_j}{1 + Jexp(-\alpha r_j + \beta b_j)}$$
$$\Longrightarrow \left(\alpha + \frac{(1 - s_j)}{(r_j - c)s_j}Jexp(-\alpha r_j + \beta b_j) + \frac{(1 - s_j)}{(r_j - c)}\left(\frac{1}{s_j} - \frac{\beta^2}{\alpha\kappa}\right)\right)\frac{\partial r_j}{\partial \beta} = \beta\frac{1}{\alpha\kappa}s_j + b_j$$

If $\alpha + \frac{(1-s_j)}{(r_j-c)}\left(\frac{1}{s_j} - \frac{\beta^2}{\alpha\kappa}\right) > 0$, then we have $\frac{\partial r_j}{\partial \beta} > 0$.

$$\alpha + \frac{(1 - s_j)}{(r_j - c)}\left(\frac{1}{s_j} - \frac{\beta^2}{\alpha\kappa}\right) > 0 \Longrightarrow \frac{\alpha(r_j - c)}{1 - s_j} + \frac{1}{s_j} - \frac{\beta^2}{\alpha\kappa} > 0 \Longrightarrow \frac{1}{(1 - s_j)^2} + \frac{1}{s_j} - \frac{\beta^2}{\alpha\kappa} > 0$$

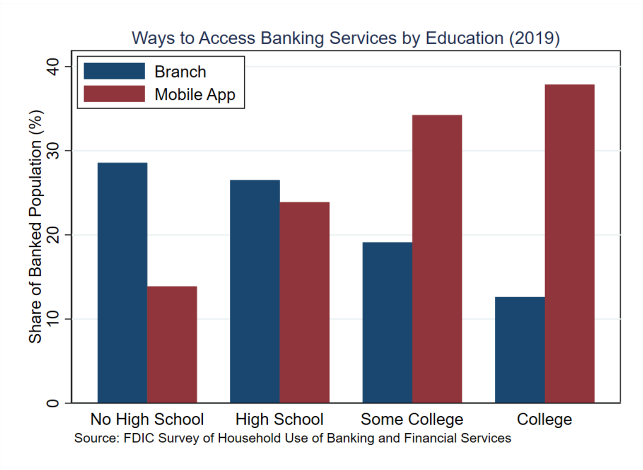
As s_j is bounded by $[0, \frac{1}{J}]$, and $\frac{1}{(1-s_j)^2} + \frac{1}{s_j}$ is monotonically decreasing in s_j. Therefore, when $J + \frac{J^2}{(J-1)^2} \geq \frac{\beta^2}{\alpha\kappa}$, we have $\frac{\partial r_j}{\partial \beta} > 0$, $\frac{\partial s_j}{\partial \beta} > 0$, and $\frac{\partial b_j}{\partial \beta} > 0$.

Bank Competition amid Digital Disruption: Implications for Financial Inclusion (Internet Appendix)

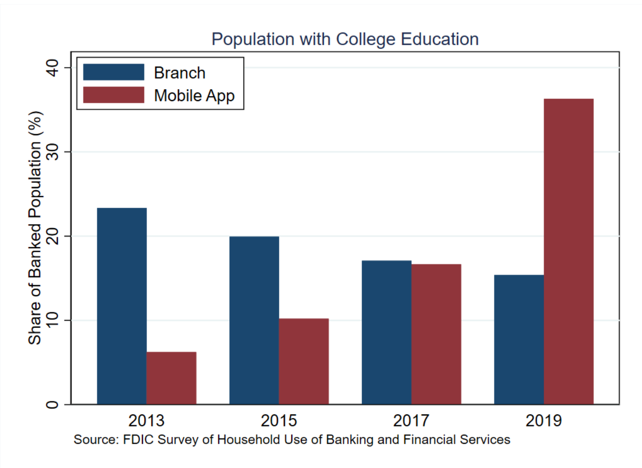
A Figures

Figure IA.1: Change of Ways to Access Banking Services—by Education

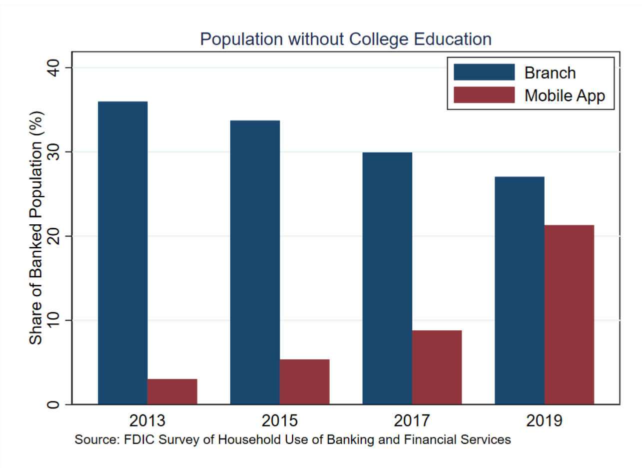
The bar charts show the ways consumers in different education buckets to access banking services. Panel (a) plots the share of survey participants that access banking services via branch and via mobile app across age distribution in 2019. Panel (a) plots the share of survey participants that access banking services via branch and via mobile app across age distribution in 2019. Panel (b) and (c) plot the same time series for young and old consumers, defined as below or above 55-year old, respectively. Source: FDIC Survey of Household Usatione of Banking and Financial Services.



(a) Across Education



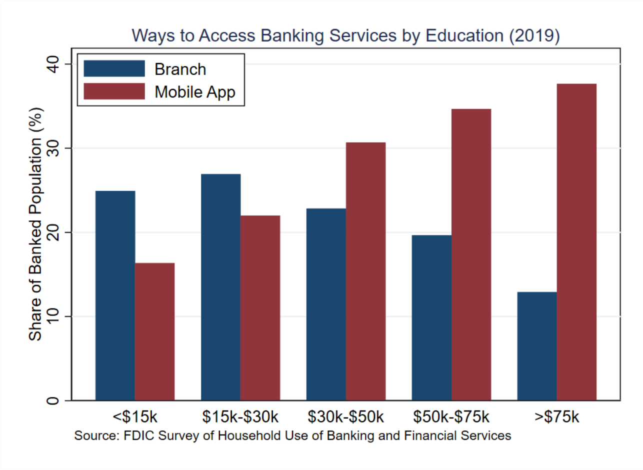
(b) More-educated



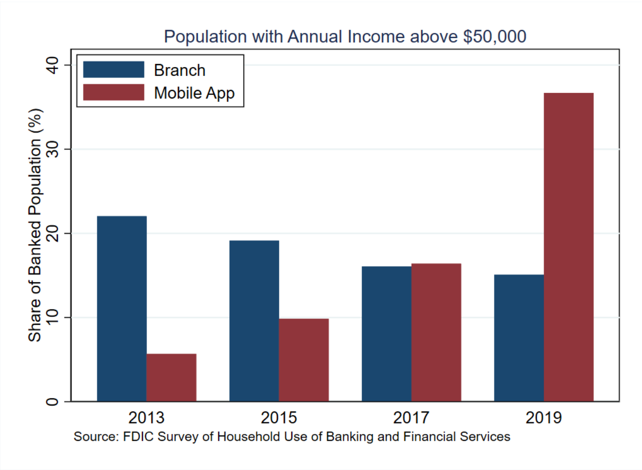
(c) Less-educated

Figure IA.2: Change of Ways to Access Banking Services—by Income

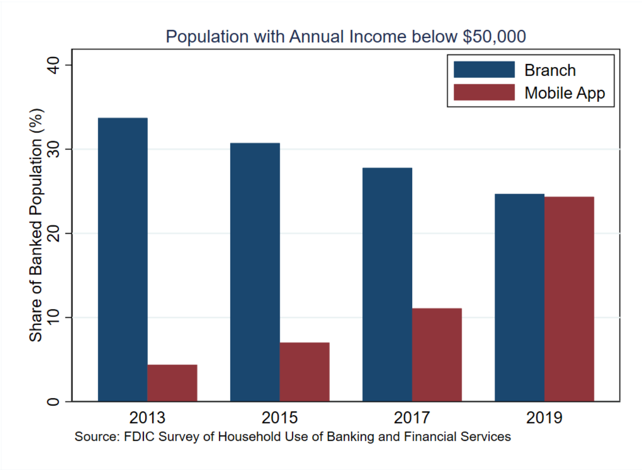
The bar charts show the ways consumers in different income buckets to access banking services. Panel (a) plots the share of survey participants that access banking services via branch and via mobile app across income distribution in 2019. Panel (b) and (c) plot the same time series for high- and low-income consumers, defined as below or above sample median, respectively. Source: FDIC Survey of Household Use of Banking and Financial Services.



(a) Across Income



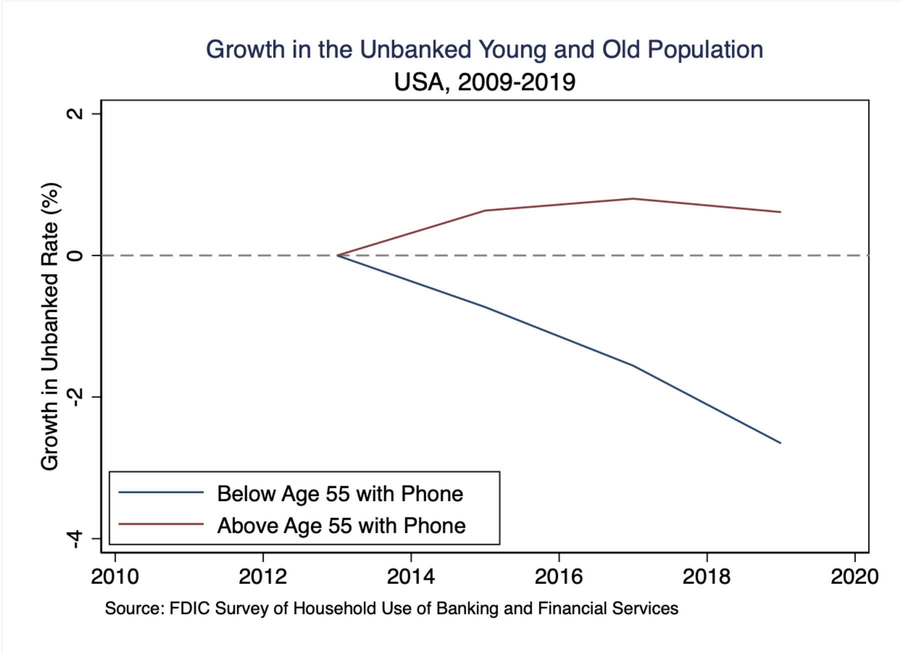
(b) High-income



(c) Low-income

Figure IA.3: Growth in the Unbanked Young and Old Population with Phone

This figure plots the growth rate of unbanked consumers under 55 versus above 55 over years with phones. Source: FDIC Survey of Household Use of Banking and Financial Services.



B Tables

Table IA.1: Bank Closure Event Study

The table reports results of the event study for county-level branch closures. The dependent variables are the same as those in Table 3. The sample only contains the treatment counties that had a sharp increase in 3G coverage, more than 50% in a single year. Post equals to 1 if the window is above 0 and zero otherwise. Standard errors are clustered at the county level. Numbers in parentheses are t-statistics. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	$\frac{\#BranchClosure_{c,t}}{\#Banks_{c,t-1}}$		$\frac{\#Branches_{c,t}}{\#Banks_{c,t-1}}$	
	(1)	(2)	(3)	(4)
Post	0.016***		−0.067***	
	(5.390)		(−6.211)	
Window $t-3$ or earlier		0.008*		−0.010
		(1.853)		(−0.555)
Window $t-2$		0.002		0.006
		(0.478)		(0.466)
Window t		0.001		−0.041***
		(0.172)		(−4.798)
Window $t+1$		0.014***		−0.087***
		(3.096)		(−6.666)
Window $t+2$		0.020***		−0.088***
		(3.856)		(−5.965)
Window $t+3$ or later		0.015***		−0.099***
		(2.990)		(−5.693)
Controls	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Observations	27,853	27,853	27,853	27,853
Adjusted R^2	0.301	0.301	0.980	0.980

Table IA.2: The Impact of 3G Coverage on Lending Competition

This table reports the effect of 3G coverage on lending competition in the lending market. The dependent variable is HHI in the odd columns and the number of lenders in the even columns. Both HHI and the number of lenders are constructed using all lenders. Columns (1)-(2) include refinancing loans; (2)-(3) home purchase loans. All columns include county and year fixed effects. Standard errors are clustered at the county level. Numbers in parentheses are t-statistics. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	Refinancing		Home Purchases	
	(1)	(2)	(3)	(4)
	HHI	log(#Lenders)	HHI	log(#Lenders)
3G Coverage	-56.063***	0.027***	-24.377	0.023***
	(-2.666)	(4.933)	(-1.290)	(4.088)
log(PerCapitaIncome)	-338.104**	-0.033	305.278**	0.026
	(-2.047)	(-1.011)	(2.468)	(0.813)
log(countyGDP)	59.507	-0.030**	-20.783	0.018
	(1.019)	(-2.175)	(-0.440)	(1.168)
log(TotalPop)	-2186.229***	1.006***	-40.384	0.170***
	(-9.240)	(16.631)	(-0.235)	(3.297)
log(TotalLoan)	524.831***	0.295***	42.679	0.197***
	(9.515)	(30.710)	(0.991)	(20.402)
County FE	✓	✓	✓	✓
State×Year FE	✓	✓	✓	✓
Observations	30,501	30,501	30,501	30,501
Adjusted R^2	0.716	0.982	0.733	0.979

Table IA.3: Effect of 3G on Lending Competition

This table reports the effect of 3G coverage on lending competition and is analogous to Table 7. The dependent variable is HHI in column (1) and the number of lenders in column (2). HHI and the number of lenders are constructed using bank lenders only. Columns (1)-(2) include all loans. All columns include county and year fixed effects. Standard errors are clustered at the county level. Numbers in parentheses are t-statistics. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	Bank Loans	
	(1)	(2)
	HHI	log(#Lenders)
3G Coverage	-44.482*	0.028***
	(-1.702)	(3.895)
log(PerCapitaIncome)	-535.949***	-0.066
	(-3.781)	(-1.623)
log(countyGDP)	-25.085	0.034
	(-0.392)	(1.406)
log(TotalPop)	-2112.810***	0.978***
	(-8.848)	(13.342)
log(TotalLoan)	169.379***	0.242***
	(3.842)	(28.268)
County FE	✓	✓
Year FE	✓	✓
Observations	30,501	305,01
Adjusted R^2	0.715	0.960

Table IA.4: Effect of 3G on Loan Pricing (All lenders)

This table reports the impact of 3G coverage on loan pricing and is analogous to Table 9. The underlying sample includes loan-level observations of all originated loans from all kinds of lenders recorded in HMDA in 2018. The outcome variable in Panel B is mortgage interest rate. In both panels, *Branch* equals 100 if the lender has a branch in the county and 0 otherwise. $\log(1 + \#Branches)$ is the logarithm of one plus the number of branches a bank has for a given county. The Unreported *Controls* include the natural logarithm of loan size, loan type, loan purpose (home purchases, refinancing or others), loan-to-value ratios, debt-to-income ratios, and borrowers' income in natural logarithm, gender, age, and race. All columns include lender fixed effects. Odd columns include state fixed effects, and even columns include county fixed effects. Standard errors are clustered at the county level. Numbers in parentheses are t-statistics. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	Panel A: Origination Fees (%)			
	(1)	(2)	(3)	(4)
Branch×3G Coverage	0.523***	0.495***		
	(8.89)	(8.86)		
log(1+#Branches)×3G Coverage			0.657***	0.678***
			(11.57)	(10.53)
log(1+#Branches)			-0.732***	-0.746***
			(-13.03)	(-11.68)
Branch	-0.811***	-0.757***		
	(-14.01)	(-13.75)		
3G Coverage	-0.880***		-0.905***	
	(-20.72)		(-21.17)	
Controls	✓	✓	✓	✓
State FE	✓		✓	
County FE		✓		✓
Bank FE	✓	✓	✓	✓
Observations	5,095,074	5,095,062	5,095,074	5,095,062
Adjusted R^2	0.239	0.240	0.239	0.240

	Panel B: Interest Rate (%)			
	(1)	(2)	(3)	(4)
Branch×3G Coverage	-0.020	-0.110*		
	(-0.17)	(-1.85)		
log(1+#Branches)×3G Coverage			-0.020	-0.105**
			(-0.22)	(-2.42)
log(1+#Branches)			0.011	0.096**
			(0.13)	(2.29)
Branch	0.019	0.119**		
	(0.17)	(2.39)		
3G Coverage	-0.064		-0.058	
	(-0.54)		(-0.51)	
Controls	Y	Y	Y	Y
State FE	✓		✓	
County FE		✓		✓
Lender FE	✓7	✓	✓	✓
Observations	5,035,302	5,035,290	5,035,302	5,035,290
Adjusted R^2	0.046	0.046	0.046	0.046

Table IA.5: Effect of 3G on Market Share of Banks with Branches

This tables tabulates the effect of 3G on the market share of bank lenders for all loans. The analysis unit is at county-year level. The dependent variable is the loan market share of lenders with at least one branch for a given county-year pair. Columns (1)-(2) include all lenders; columns (3)-(4) include entry lenders; and columns (5)-(6) include incumbent banks. Even columns include the interaction term between 3G and young county which is a dummy variable indicating that a county's median age is below 40. All columns include year, state-year, and county fixed effects. Standard errors are clustered at the county level. Numbers in parentheses are t-statistics. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	Market Share of Banks with Branches	
	(1)	(2)
3G Coverage	-1.080**	-0.582
	(-2.218)	(-1.013)
Young County × 3G Coverage		-1.174**
		(-2.004)
Young County		0.477
		(0.746)
log(PerCapitaIncome)	-4.035*	-4.388**
	(-1.843)	(-2.005)
log(countyGDP)	-0.887	-0.878
	(-0.815)	(-0.809)
log(TotalPop)	-17.900***	-15.898***
	(-3.793)	(-3.311)
log(TotalLoan)	3.210***	3.186***
	(5.181)	(5.142)
County FE	✓	✓
Year FE	✓	✓
Observations	30,501	30,479
Adjusted R^2	0.791	0.793

Table IA.6: Distributional Effect of 3G on Loan Pricing across Age Groups (All Lenders)

This table reports the interaction effect between 3G coverage and borrower age on loan pricing using loans originated by all lenders. The table is analogous to Table 12. The analysis unit is at the loan level. The dependent variable is the loan origination fees in columns (1)-(2), and the loan interest rates in columns (3)-(4). The key independent variables of interest are the interaction term between 3G coverage and indicator variables for borrowers' age range. The Unreported *Controls* include the natural logarithm of loan size, loan type, loan purpose (home purchases, refinancing or others), loan-to-value ratios, debt-to-income ratios, and borrowers' income in natural logarithm, gender, age, and race. All columns include lender fixed effects. Odd columns include state fixed effects, and even columns include county fixed effects. Standard errors are clustered at the county level. Numbers in parentheses are t-statistics. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	Origination Fees		Interest Rate	
	(1)	(2)	(3)	(4)
3G Coverage	-0.978***		-0.137*	
	(-17.47)		(-1.91)	
34<Borrower Age<55×3G Coverage	0.142***	0.147***	0.205**	0.209**
	(3.43)	(3.65)	(2.34)	(2.33)
Borrower Age>54×3G Coverage	0.318***	0.300***	-0.0168	0.00927
	(5.05)	(4.84)	(-0.08)	(0.05)
34<Borrower Age<55	-0.0687*	-0.0789**	-0.141**	-0.142**
	(-1.73)	(-2.05)	(-2.39)	(-2.31)
Borrower Age>54	-0.242***	-0.234***	0.117	0.0915
	(-4.10)	(-4.04)	(0.37)	(0.31)
Controls	✓	✓	✓	✓
State FE	✓		✓	
County FE		✓		✓
Lender FE	✓	✓	✓	✓
Observations	5,095,074	5,095,062	5,035,302	5,035,290
Adjusted R^2	0.239	0.240	0.0459	0.0456