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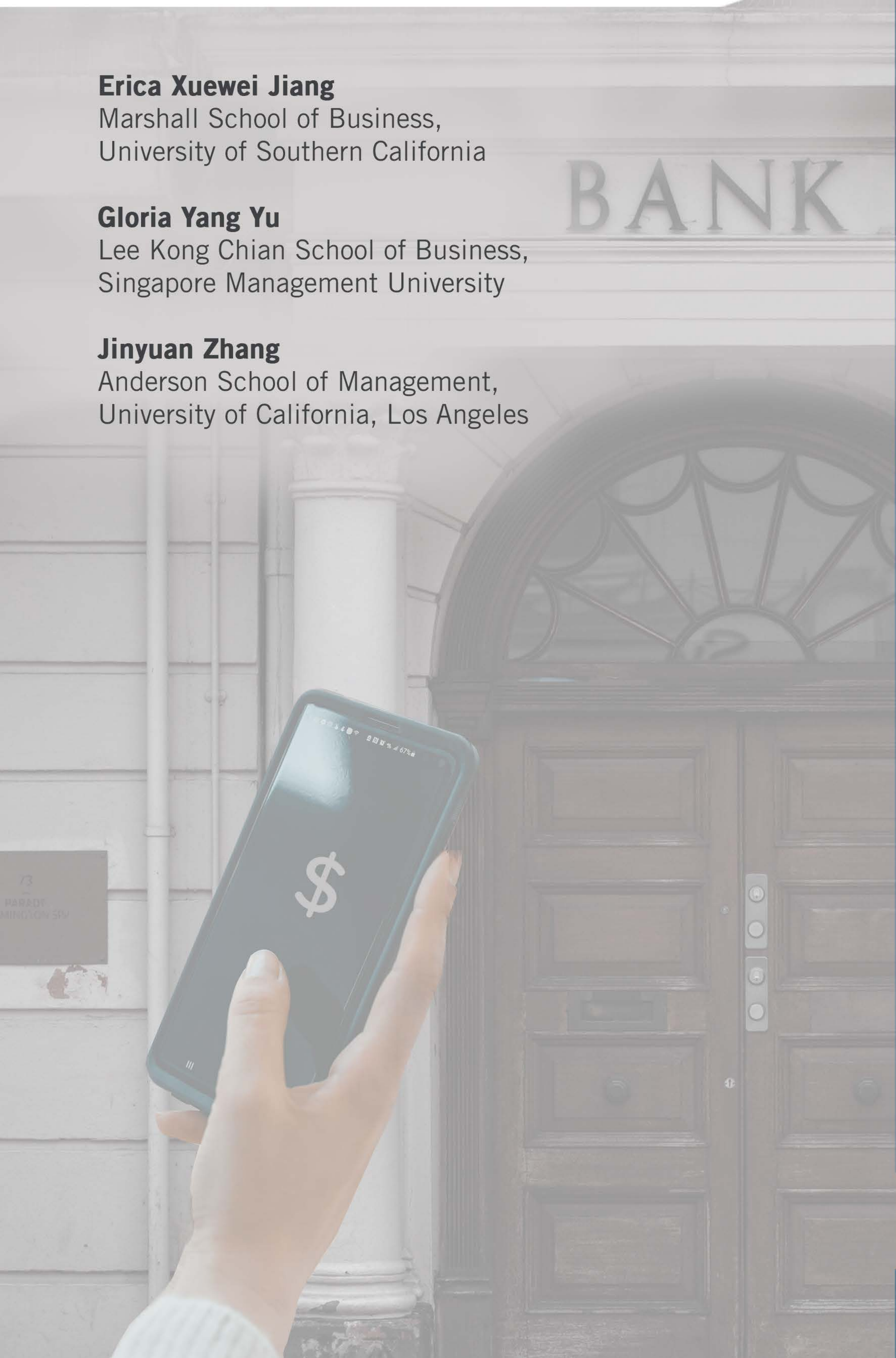
# Bank Competition amid Digital Disruption: Implications for Financial Inclusion


**Erica Xuewei Jiang**
Marshall School of Business,
University of Southern California

**Gloria Yang Yu**
Lee Kong Chian School of Business,
Singapore Management University

**Jinyuan Zhang**
Anderson School of Management,
University of California, Los Angeles



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# Bank Competition Amid Digital Disruption: Implications for Financial Inclusion

Erica Xuewei Jiang, Gloria Yang Yu, and Jinyuan Zhang*

**Abstract**

We study how digital disruption impacts bank competition, considering consumers' heterogeneous digital preferences. Exploiting the rollout of 3G mobile networks, we find that digital disruption geographically expands bank lending but contracts bank branch networks. Meanwhile, more (less) branch-reliant banks increase (decrease) prices. These developments result in a distributional effect, reducing the unbanked rate among young consumers while increasing it among the elderly. A structural model shows that increased digital preference of young borrowers drives banks' branch adjustment, causing significant surplus losses for older savers. Regulating branch closures could mitigate the distributional impact as the banking sector undergoes digital transformation.

*Keywords*: technology, bank competition, consumer preference, digital inequality, financial inclusion

*JEL*: D40, G21, O30

*Jiang is from the University of Southern California, Marshall School of Business. erica.jiang@marshall.usc.edu. Yu is from the Singapore Management University. gloriayu@smu.edu.sg. Zhang is from the UCLA Anderson School of Management. jinyuan.zhang@anderson.ucla.edu. We thank Kenneth Ahern, Greg Buchak, Matteo Benetton, Philip Bond, Chad Syverson, Sean Higgins, Marco Di Maggio, Andrea Eisfeldt, Daniel Grodzicki, Valentin Haddad, Barney Hartman-Glaser, Gerard Hoberg, Rawley Heimer, Gregor Matvos, Shaun McRae, Yueran Ma, Clemens Otto, Andrea Pozzi, Amit Seru, Amir Sufi, Anthony Lee Zhang, the seminar participants at University of Chicago Booth, CKGSB, Columbia GSB, NY Fed, Dartmouth Tuck, Northwestern Kellogg, IWH-Halle, OCC, FDIC, University of Washington, UCLA Anderson, USC Marshall, Singapore Management University, and the conference participants at NBER Household Finance SI, SITE Financial Regulation and IO of Healthcare and Consumer Finance Markets, Workshop on Financial Intermediation and Regulation, AEA, Utah Winter Finance, NYU WAFIN, NFA, Yale Junior Finance Conference, Columbia Workshop in New Empirical Finance, BSE Summer, CICF, and IIOC for helpful comments. Runtong Cai provided outstanding research assistance. Yu thanks the support of the Sim Kee Boon Institute for Financial Economics at SMU. *First version: Feb, 2022.*

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# 1 Introduction

The widespread adoption of technology has transformed the way financial intermediaries operate and has raised important questions about its impact on financial inclusion.[1] While it is widely believed that technology can democratize access to financial services and increase competition among intermediaries (Philippon, 2016, 2019), there is a growing recognition that not all consumers have equal access to digital services due to limited technological skills or inability to afford digital devices. Survey responses reveal a previously overlooked divergence in how consumers access banking services, with younger and higher-income consumers adopting digital platforms, while older and lower-income consumers still prefer bank branches (Figure 1).

Motivated by this observation, we study *how* banks compete amid digital disruption, when consumers have heterogeneous preferences for digital services, and the resulting distributional effects. We empirically analyze the effects of digital disruption on bank branching, pricing, and entry decisions as well as on financial inclusion. To quantify the effect on consumer surplus, we develop a structural model that matches the reduced-form results. Our findings show that following digital disruption, consumers who value digital services benefit from intensified bank competition, while the surplus of consumers who value bank branches significantly declines due to banks' optimal price and branch adjustments. This distributional effect echoes policymakers' rising concern about digital inequality.[2] Finally, we discuss a possible policy intervention through a counterfactual analysis, which could alleviate the distributional impact the banking sector undergoes digital transformation.

Our empirical analysis is guided by the following conceptual framework. Prior to the advent of digital disruption, all consumers valued bank branches. Advancements in technology have improved the quality of digital banking services, making branches less valued by some consumers who are more tech-savvy. Although there are still consumers that value branches, banks optimally close some branches as the overall preference for branches declines. Meanwhile, the enhanced digital service quality increases the profit margin of banks that do not rely on branch networks, inducing the entry of such banks. The intensified competition makes it sub-optimal for more branch-reliant banks to compete on prices. Instead, they continue providing high-quality in-branch services to cater to consumers who value branches.

This new market landscape leads to diverging pricing strategies. On the one hand, the intensified competition forces less branch-reliant banks to lower prices. On the other hand,

[1] See, for example, United Nation's discussion and How to Close the Digital Divide in the U.S.
[2] See, for example, From the 'Digital Divide' to 'Digital Inequality'.



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as banks close branches following digital disruption, consumers that value branches are left with limited choices. Facing more inelastic demand, more branch-reliant banks optimally charge higher prices. Consequently, while tech-savvy consumers benefit from intensified bank competition, non-tech savvy consumers suffer from the reduced number of branches and pay higher costs to access banking services.

The first part of this paper provides empirical evidence for the above conceptual framework by exploiting the staggered introduction of the third-generation (3G) mobile networks. The expansion of 3G accelerated banks' digitization process and fostered the rise of mobile banking. As the 3G infrastructure was slowly constructed across the U.S., this setting provides variations in both the time series and the cross-section.

We begin by examining the impact of 3G expansion on the branching, entry, exit, and pricing of banks. In a staggered difference-in-difference (DiD) setting, we find that the expansion of 3G networks leads to a contraction of bank branches, especially in counties with younger population. Quantitatively, the total number of branches decreases by 1.4% after the 3G network fully covers a county. Across counties, more than twice the number of branches close in counties with more younger population than in counties with less younger population. The contraction of branch networks leads to a more consolidated branch network within a region, which is primarily driven by the effect of 3G in counties with younger populations. Yet, despite the more concentrated local branch networks, consumers have access to a greater number of banking service providers. We find that as 3G fully covers a region, there are 2.7% more banks serving the area. The county-level findings are consistent with 3G expansion allows less branch-reliant banks to contract branch networks and remotely serve consumers.

We then examine heterogeneity in banks' responses to digital disruption, which helps draw insights into the underlying transformation in the banking industry. Conceptually, the decision of whether or not to maintain branches may depend on the value that a bank's customers place on them. Banks that focus on customers who value local branches may view branch service as critical to retaining their customers; we refer to these banks as more branch-reliant. Conversely, banks that focus on customers who primarily use digital platforms may require fewer branches; we refer to these banks as less branch-reliant. We acknowledge that a bank's decision to operate as more or less branch-reliant is a strategic choice made historically. While banks may adjust their business models, such adjustments are often costly and require significant resources.

To capture the degree to which banks rely on branches, we measure their branch reliance as the number of branches required to serve every million dollars of deposits in 2007. Using this measure, we categorize banks as less branch-reliant if they fall in the lowest quartile



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of the branch-reliance index, and as more branch-reliant otherwise. Our findings suggest that less branch-reliant banks contract their branch networks by 4% after the expansion of 3G networks, while more branch-reliant banks do not downsize their branch networks as much. These structural changes are accompanied by diverging pricing responses among banks. Specifically, more branch-reliant banks increase the interest rate on the loan product and offer lower deposit rates (i.e., charge higher rate spreads), while less branch-reliant banks decrease the interest rate on the loan product and offer higher deposit rates.

These findings reveal a new banking market structure emerging after 3G expansion. Banks *without* a comparative advantage in operating branches compete on prices and serve consumers that prefer digital services, while banks *with* a comparative advantage in operating branches invest in branches, charge higher prices, and serve consumers that value branch services. A potential endogeneity concern is that omitted factors drive both 3G network expansion and banking decisions.

To address this concern, we exploit an instrumental variable (IV) strategy, following Manacorda and Tesei (2020) and Guriev et al. (2021). We construct a Bartik instrument by multiplying local lightening strike frequency by the number of years since 2007, where lightning strike frequency is the cross-sectional accounting identity, and year is the time-series accounting identity that captures the growth of 3G in the aggregate economy. Frequent lightning strikes substantially increase the maintenance costs of 3G network providers, and hence, slowed down the rollout of 3G construction. Based on a battery of tests, we show that the IV plausibly satisfy the exclusion restriction, having no impact on banks' decisions or local economic growth through channels other than IT diffusion. IV regressions confirm the causal impact of the expansion of 3G networks on bank branching, entry, and pricing decisions.

This new banking landscape has implications for the distributional effect across heterogeneous consumers. In the second part of the paper, we examine the consequences for consumers. Using survey data, we find that after the 3G expansion, consumers under the age of 55 are 16.7% less likely to be unbanked or underbanked, while consumers above the age of 55 are 11.9% more likely to be unbanked or underbanked. These effects are particularly significant for consumers whose annual family income is less than $30,000. Our findings suggest that low-income and senior consumers, who are more likely to continue using branches after the expansion of 3G networks according to their survey responses, are at a higher risk of financial exclusion as the banking sector undergoes digital transformation.

We then build a structural model to quantify the distributional effect of digital disruption on consumer surplus. The model incorporates several realistic features of both the supply and



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demand. On the demand side, consumers have different price sensitivities and heterogeneous preferences for branches and digital services, and these demand characteristics may vary across deposit and loan markets.[3] While banks may have separate pricing strategies for the two product types based on the corresponding demand, bank branching decisions depend on the total value of branches in both markets as a branch usually serves both markets. These features of the demand and supply may have important implications on consumer surplus.

The basic model framework is developed in the spirit of Berry et al. (1995).[4] Our main innovation is to model banks' endogenous pricing, branching, and entry decisions simultaneously. Specifically, banks compete to set prices for deposit and loan products while choosing the number of branches at some cost. Consumers with heterogeneous preferences choose banking services to maximize their indirect utilities, which are functions of both price and convenience, as captured by the number of branches and digital quality. Given that consumers value branch services, banks optimally choose the number of branches that allow them to charge higher markups.

Using data before 3G expansion, we estimate the model to obtain the pre-shock structural parameter values. We then calibrate the changes in parameters to match the model-predicted moments with the effects of 3G expansion identified in the reduced-form analysis. The estimated preference for branches is larger for older consumers in both deposit and loan markets. This result is consistent with the survey finding that older consumers are more likely to use branches to access their bank accounts. We also find that young depositors derive more utility from digital services than older depositors, while the difference in preferences for digital services between young and old borrowers is insignificant in the pre-shock sample. This is not surprising, as traditional mortgage origination was barely conducted on digital platforms before the introduction of 3G networks. Finally, our calibration results indicate that the expansion of 3G networks has a more substantive effect on the improvement of digital service quality than on cost reduction. The perceived digital service quality by young consumers increased by 59% in the loan market and 20% in the deposit market, while the reductions in marginal costs were less than 1%.

We then use the estimated model to quantify the distributional effect resulting from banks' responses to digital disruption. We find that young depositors' surplus improves by 0.95 cents for every dollar of deposits saved, while old depositors' surplus declines substantially by 7 cents for every dollar of deposits. A part of this surplus decline is due to the

[3]For example, the pool of depositors consists of more older people who likely value branches, while the borrower pool contains more younger people who likely value digital services. Moreover, the branch reliance may be different across the two markets, even for the same consumer, due to the service nature.

[4]The discrete choice model in Berry et al. (1995) has been applied to the banking sector in Buchak et al. (2018a); Jiang (2019); Xiao (2020); Benetton (2021) and Robles-Garcia (2019).



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higher unbanked rate among older households, which increases by 0.15 percentage points, representing a 6.3% increase relative to the pre-shock average unbanked rate. In the loan market, both old and young borrowers are less likely to obtain credit from banks. Since both young and old borrowers value branch services in the loan market, their surplus reduces due to branch closure.[5] However, young borrowers are partially compensated by relatively cheap loans offered by less branch-reliant banks.

Our model enables us to analyze how digital disruption in one market affects the other market through the banks' optimal responses to the changing environment. In our counterfactual exercise, we find that if digital disruption had only occurred in the deposit market, old depositors would not have been worse off. This is because the depositor pool has a relatively larger share of old consumers, and the same amount of digital improvement and cost reduction of banks may not be large enough to affect bank entry and exit in the market. However, since the borrower pool has more young consumers who value digital services, digital disruption in the loan market lowers the marginal benefit of branches in the loan market. When the loan market experiences digital disruption, less branch-reliant banks close branches, and more branch-reliant banks exit the market, spilling the shocks from the loan market to the deposit market and making old depositors worse off.

Finally, we disentangle how different bank responses contribute to the distributional effect to shed light on possible policy interventions. Our analysis shows that banks' optimal branch adjustment is the main driver of the distributional effect. This motivates a policy counterfactual analysis, in which we impose a cap on the percentage of branches that are allowed to close. We compare the effects of digital disruption with and without such a branch closure regulation. As the regulation binds, banks increase prices to cover branch cost. Despite higher prices, old consumers, especially old depositors, benefit from the regulation because of their strong preference for branches and low price sensitivity. Overall, the regulation leads to a substantial increase in total consumer surplus by imposing stricter restrictions on branch closures.

Our paper contributes to several strands of literature. First, our research question connects to the broader literature on the distributional consequences of technological disruption (Eizenberg, 2014; Kogan et al., 2017; Jaravel, 2019) and industrial challenge for the digital age (Tirole, 2020). We focus on the impact of technological innovation on banking and financial inclusion, which has been established to have a profound impact on the real economy and consumer welfare.[6] We contribute to this literature by examining the interplay

[5]Note that this change of surplus does not include the calibrated effect of improved digital quality.

[6]See, for example, Beck et al., 2007; Kashyap and Stein, 2000; Allen et al., 2016; Khwaja and Mian, 2008; Mian and Sufi, 2009.



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between the traditional banking business model and the changing landscape and empirically and quantitatively study the distributional effects as the banking sector undergoes digital transformation.

The traditional banking business is local, in which branches play a crucial role in promoting financial inclusion and local economic development.[7] As financial technology advances (Chen et al., 2019; Goldstein et al., 2019; Buchak et al., 2018b; Fuster et al., 2019), banking has been undergoing a digital transformation (He et al., 2021; Berg et al., 2022).[8] The theoretical literature argues that digital disruption will increase competition and improve consumer welfare (Philippon, 2016, 2019; Vives and Ye, 2023).[9] Supporting evidence has been found in developing countries (D'Andrea and Limodio, 2023; Crouzet et al., 2019; Higgins, 2022; Pierre et al., 2018; Bachas et al., 2021).

Our study is the first, to our knowledge, to provide empirical evidence that digital disruption may negatively impact tech-unsavvy consumers as some banks optimally close branches and increase prices in response to digital disruption. The finding has important implications for policymakers and financial institutions seeking to promote financial inclusion through technology. In support of our finding, Sakong and Zentefis (2022) use geolocation data to show that the distance between a household's home and the nearest branch affects their branch usage, which directly supports the potentially pronounced implications of our findings about branch closures for non-tech savvy consumers. Our findings are consistent with the theoretical arguments of Parlour et al. (2022) and Chen and Riordan (2008) and complementary to empirical research that studies the benefits and costs of fintech and digital services (Cong et al., 2023; Crouzet et al., 2019; Buchak et al., 2021; Chen and Jiang, 2022).

Finally, we contribute to a growing literature that studies banking industrial organization in the context of household finance. Our structural model shows that a technology shock in the lending market, which disproportionately affects younger generations, can result in negative spillover effects to older generations in the deposit market. This underscores the need to consider the intergenerational impacts of technology adoption, particularly in the context of financial markets with diverse customer bases. Existing papers have studied how bank competition affects consumer welfare in the mortgage market (Scharfstein and Sunderam, 2016; Buchak et al., 2018a; Benetton, 2021; Jiang, 2019; Allen et al., 2019; Robles-

[7]See, for example, Petersen and Rajan (2002); Beck et al. (2010); Célerier and Matray (2019); Stein and Yannelis (2020); Brown et al. (2019); Jayaratne and Strahan (1996); Huang (2008); Jayaratne and Strahan (1997); Allen et al. (2021); Bruhn and Love (2014); Allen et al. (2021); Carlson and Mitchener (2006); Ji et al. (2022).

[8]Historically, the banking sector has seen technological advancements, such as the introduction of ATMs. Berger and DeYoung (2006), Berger (2003), and Berger and Mester (2003) study how technological progress affected the banking industry before 2000.

[9]For surveys on technological disruption in banking and its potential impact on efficiency and customer welfare, see Stulz (2019) and Vives (2019).



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Garcia, 2019), deposit market (Egan et al., 2017; Drechsler et al., 2017; Xiao, 2020), payment (Whited et al., 2022; Li, 2023; Wang, 2022), credit card (Nelson, 2018), personal loans (Cuesta and Sepúlveda, 2021), and auto loans (Yannelis and Zhang, 2021). Our model also points out branching decisions as an important channel through which banks' deposit-taking interacts with loan-making, adding to the existing banking literature that primarily focuses on the balance sheet channel (Corbae and D'Erasmo, 2019; Wang et al., 2022; Diamond et al., 2020) or the synergies between multiple products offered by banks (Egan et al., 2022; Aguirregabiria et al., 2017; Benetton et al., 2022)

## 2 Conceptual Framework

There are two consumer groups with different preferences for banking services. Non-tech savvy consumers have a preference for branch services, whereas tech-savvy consumers prefer digital services. To obtain banking services, they choose between two types of banks with different business models. More branch-reliant banks can more efficiently operate physical branches, while less branch-reliant banks provide superior digital services.

In the pre-digital disruption era, both non-tech-savvy and tech-savvy consumers place a high value on branch services, as digital services lack the quality necessary to meet their needs. However, subsequent technological advancements significantly improve the quality of digital services, which makes less branch-reliant banks more attractive to tech-savvy consumers. In line with this framework, there has been a shift over the past decade in the primary method of accessing banking services from branches to digital platforms, as illustrated in Figure 1. This shift has been primarily driven by tech-savvy consumers who are younger, wealthier, or better-educated, as indicated in Table A2.

The changes brought about by technological advancements fundamentally reshape the banking industry. While there are still consumers who value branch services, banks optimally close some branches as the overall preference for branches declines. Moreover, the improvement in digital service quality increases the profit margin of less branch-reliant banks, leading to an influx of such banks in the market. The intensified competition makes it suboptimal for more branch-reliant banks to compete on prices. Rather, they continue providing high-quality in-branch services to attract consumers who value branches.

This new market structure allows banks to effectively price discriminate against consumers. On the one hand, the intensified competition forces less branch-reliant banks to lower prices. On the other hand, as banks close branches following digital disruption, con-



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sumers that value branches are left with limited choices. Facing more inelastic demand, more branch-reliant banks optimally charge higher prices. Consequently, while tech-savvy consumers benefit from intensified bank competition, non-tech savvy consumers suffer from the reduced number of branches and pay higher costs to access banking services.

# 3 Institutional Background and Data

## 3.1 3G Expansion

The 3G technology was the first high-speed mobile network generation that served as a viable alternative for internet browsing, which drove the growth in broadband subscriptions and popularizes many digital services.[10] Specific to the banking sector, many banks introduced their first versions of digital banking in early 2000.[11] Yet, banking services provided on digital platforms were limited at that time.

The expansion of 3G technology accelerated the digitization process of banks and facilitated the rise of mobile banking. With its greater speed, capacity, and security, 3G networks were a significant improvement over previous mobile networks and enabled upgraded mobile banking to meet consumers' heightened demands for efficient and timely financial transactions and record access.[12] As a result, it is plausible that 3G expansions changed consumers' preferences for bank branches both at the extensive margin by affecting the probability of obtaining banking services via digital channels and at the intensive margin by influencing the frequency of using bank branches. We will discuss this in detail in Section 3.3.

## 3.2 Data and Summary Statistics

We combine several data sets. We briefly introduce these data sets below and provide greater detail in Appendix A. Table 1 presents the summary statistics.

**3G Network Coverage** We use 3G network coverage digital maps from 2007 to 2018

[10] According to OECD data in 2013, mobile broadband subscriptions in OECD regions experienced year-over-year growth of 16.63 percent, with total subscriptions being more than double those of fixed wired broadband.

[11] The first mobile banking service was launched in 1997 by Merita Bank of Finland offering SMS text banking. In 1999, the Bank of Internet USA stated the purpose of an internet-based bank. By 2006, 80% of all U.S. banks provided mobile banking services.

[12] For example, the upgraded mobile banking allowed users to manage their accounts, apply for products (e.g., credit cards and loans), pay digitally, and access customer service (e.g., text, audio, or video chat) anywhere at any time. It supported personalization (e.g., preferred language, default transactions, alerts, chatbots, and online support). In recent years, mobile banking has expanded into other portal devices beyond phones (e.g., tablets and watches). In comparison, online banking enabled by fixed wired broadband is limited to laptops or personal computers which are not easily portable.



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provided by Collins Bartholomew's Mobile Coverage Explorer (Guriev et al. 2021). These maps gather coverage data that mobile network operators submit to the GSM Association, and provide an indicator variable identifying the availability of 3G for each 1×1-kilometer binary grid cell. 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 local population density, measured using a NASA map of population density for each 1×1-kilometer grid cell across one county's polygon. This measure captures the proportion of the population covered by 3G networks in one county.

Our empirical analysis exploits the timing of 3G expansion. Figure 2 illustrates the staggered geographic expansion of 3G networks at the county level over our sample period. The west coast witnesses 3G expansion slightly earlier. Overall, 3G coverage increased from 3.71% in 2007 to 86.1% in 2018, with the most significant annual increase occurring in 2011.

**The FDIC Survey of Household Use of Banking and Financial Services** We use the FDIC Survey data to document stylized facts about households' use of digital and branch banking services as well as to study the effect of 3G expansions on financial inclusion. The Survey has been conducted biennially since 2009, but several questions were introduced after 2009. Each survey collects responses from around 33,000 consumers about questions related to their bank account ownership, the usage of non-bank transaction and credit services, the primary methods they use to access their bank accounts if they are banked, and the saturated set of demographic information. Like other survey data, it weighs each response to indicate how representative the survey participant is in the full population, which helps scale up the survey results to reflect the entire economy.

**FDIC Summary of Deposit.** We obtain data about bank branches and branch-level deposits from the FDIC Summary of Deposit. The FDIC collects these pieces of information from all FDIC-insured institutions as of June 30 each year.

**Home Mortgage Disclosure Act.** We obtain loan-level mortgage origination data from the Home Mortgage Disclosure Act (HMDA) database. The HMDA includes the majority of residential mortgage applications in the U.S.

**RateWatch.** We obtain branch-level deposit and loan pricing data from RateWatch. RateWatch collects deposit and loan product interest rates at the bank branch level. We obtain the interest rates charged on 12-month certificated deposit accounts with an account size of $25,000 and saving accounts with an account size of $2,500, as well as a variety of mortgage loans, auto loans, and uninsured credits. Detailed information on these can be found in Appendix A.



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**The World Wide Lightning Location Network (WWLLN).** We use the lightning strike data to construct our instrument. We obtain the exact coordinate and timestamps of all detected lightning strikes throughout the U.S. from 2007 to 2018. To measure the degree to which a county is affected by lightning strikes, we calculate the amount of the population annually affected by lightning strikes in a county and divide it by the total local population. The measure reflects the proportion of the population potentially affected by lightning strikes in each county.[13]

**Others** County-level demographic features, including GDP, population, and employment are collected from the U.S. Bureau of Economic Analysis (BEA).

### 3.3 Household Use of Banking Services and Digital Divide

We use the FDIC Survey data to document several stylized facts about households' use of banking services. Figure 1 shows a decline in the share of the population that relies on branches as their primary means of accessing their bank accounts, from 29.75% in 2013 to 18.75% in 2019. Meanwhile, the use of digital banking, which encompasses both mobile and online banking, has increased from 41.35% to 59.12% during the same period. This increase has been largely driven by the growing adoption of mobile banking, which rose from 6.27% in 2013 to 35.63% in 2019.

Individuals who prefer digital services are younger, wealthier, and more-educated, as compared to people who value branches (Table A2). In 2019, 50.21% of consumers under 55 years of age shifted to mobile banking services, while only 13.78% of consumers above 55 years of age choose mobile banking. The rising popularity of digital banking is associated with the expansion of 3G networks. As Table A1 shows, a household is 48% less likely to use branches as her primary way of accessing bank accounts as 3G fully covers the metropolitan statistical area (MSA) of her residence.

## 4 Digital Disruption and Banking Industry

In this section, we present empirical evidence about the impact of digital disruption on the branching, pricing, entry, and exit of banks. Firstly, we present county-level evidence. Next, we analyze the impact on individual banks and their heterogeneous responses. Finally, we

[13] Note that this measure is zero if no one lives in the region with frequent lightning strikes. Moreover, if a region is hit by lightning strikes multiple times, we repeatedly count the affected population. Thus, this measure is not bounded by 1.



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discuss the identifying assumptions and address the remaining endogeneity concerns using an IV approach.

## 4.1 County-Level Evidence

We begin by presenting county-level evidence of the digital disruption impact on the banking industry. Figure 3 shows the dynamic impact of 3G expansion on local branch closures and mortgage market competition. We conduct an Difference-in-Difference (DiD) event study:

$$Y_{c,t} = \sum_{\tau=-5}^{\tau=6} \beta_\tau \mathbb{I}_{c,\tau} \times \text{Treat}_c + \lambda X_{c,t-1} + \mu_c + \nu_{s,t} + \epsilon_{c,t}. \tag{1}$$

$Treat$ is an indicator variable and set to one if county $c$ experiences an increase in 3G coverage of over 50% within our sample period, and zero otherwise. $\mathbb{I}_{c,\tau}$ is an indicator for whether year $t$ is $\tau$ year since county $c$ experiencing a 50% increase in 3G coverage. $X_{c,t-1}$ is a vector of lagged county controls. $\mu_c$ and $\nu_{s,t}$ are county fixed effects and state-year fixed effects, respectively.

After a sharp increase in 3G coverage, counties experience a significant and sustained decline in the number of branches (Panel a). This decline in branches is not observed prior to the 3G expansion, indicating that it is likely not due to hidden economic factors that also influence the 3G expansion. The branch closures are accompanied by an increase in local branch concentration, as fewer banks own a larger share of branches (Panel b).[14]

There is no evidence to suggest that the contraction of bank branch networks leads to increased concentration in local product markets. Panels (c) and (d) present findings from the residential mortgage market, where a sharp 3G network expansion is associated with a decline in the Herfindahl-Hirschman Index (HHI) and an increase in the number of lenders. These effects persist for several years. In contrast, the effects are negligible and statistically insignificant during the three-year period before the event.

We propose that the absence of a decrease in local market competition can be attributed to digital disruption, which expands the geographic scope of bank competition from local to national levels. Digital disruption enables banks to serve consumers remotely without the need for a local branch, which makes it easier for more banks to enter and compete in each local market. Supporting this hypothesis, Figure 4 illustrates that lenders have

[14] We measure branch concentration as the sum of the squared share of branches owned by each bank ($j$) in a county, $\sum_j (\frac{Branch_j}{\sum_j Branch_j})^2$.



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become increasingly dispersed geographically over the past decade. From 2009 to 2017, the entire distribution of the number of counties covered by each lender shifted rightward (Panel a), and the mass of lenders' geographic concentration has moved closer to zero, indicating that they are more geographically dispersed (Panel b).[15] The average number of counties covered by each lender increased by about 50% from 2009 to 2017. The average geographic concentration declined by 21% since 2009.

**Dynamic Panel Difference-in-Difference Analysis** To gain a more comprehensive understanding of the impact of digital disruption on the banking industry, we employ a dynamic panel setting to conduct difference-in-difference (DiD) analysis. This approach leverages both the time-series and cross-sectional variations in the 3G expansion across U.S. counties to provide a more nuanced analysis. We estimate the following specification:

$$\text{County level: } Y_{c,t} = \beta \text{3G Coverage}_{c,t} + \lambda X_{c,t-1} + \mu_c + \nu_{s,t} + \epsilon_{c,t}. \tag{2}$$

The key variable of interest is *3*G Coverage$_{c,t}$, which is the share of the population with potential access to 3G in county $c$ in year $t$. $X_{c,t-1}$ is a vector of one-year lagged local economic variables that may affect the speed of the 3G network expansion. $\mu_c$ and $\nu_{s,t}$ are county fixed effects and state-year fixed effects, respectively. The inclusion of these fixed effects makes the specification feature a DiD design that exploits the cross-sectional variation in the 3G coverage changes that occur within a state year. We estimate this specification for various county-level outcome variables.

Panel A1 of Table 2 presents the bank branch network results. On average, a 100% increase in 3G coverage leads to a 1.4% reduction in the total number of bank branches in a county (column 1).[16] It is worth noting that the OLS estimate may underestimate the impact of the 3G expansion on branch outcomes due to the tendency of internet providers to offer services in affluent areas where branch services are in high demand. Despite this limitation, the estimate still suggests a significant impact: the aggregate number of branches dropped by 9% over this sample period, while our estimate suggests that the 3G expansion contributed to 15.6% of this decrease.

[15] We measure the geographic concentration of a lender $j$ as the sum of the squared share of the mortgage origination activity in each county: $\sum_{\mathbb{K}j}(\frac{Volume_{jk}}{\sum_{\mathbb{K}j} Volume_{jk}})^2$, where $\mathbb{K}j$ is the set of counties in which lender $j$ has originated at least one mortgage loan, and Volume$_{jk}$ is the total loan amount originated by lender $j$ in county $k$.

[16] We transform the outcome variable, number of branches, by taking its logarithm and adding one to address the issue of zeros. To test the robustness of our results, we explore different transformations, such as inverse hyperbolic sine and Pseudo-Poisson Maximum Likelihood. Despite the different transformations, we find consistent results, and the estimated effects are similar. Since zero counts are not prevalent in our study, we use the log(1+x) transformation for simplicity and to accommodate instrumental variables and numerous fixed effects in our analysis.



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We then examine the heterogeneous effects across counties by estimating the same specification using county subsamples. Columns 2 and 3 use subsamples of counties with more and less younger population, respectively. The sample used for column 2 (3) includes counties whose shares of the population under age 55 are in the top three quartiles (bottom quartile). Our findings show that the introduction of 3G leads to more branch closures in counties with a younger population. Quantitatively, the number of branch closures was more than twice as high in young counties compared to old counties.

The findings indicate that technological advancements result in a reduction in bank branches, particularly in counties with a larger proportion of young individuals who are technologically savvy. Consequently, there has been a consolidation of branch networks in regions, with an increase in county-level branch concentration by 0.02 standard deviations following complete 3G coverage (Column 4). A breakdown of the results using split samples shows that this trend is mostly driven by the impact of 3G in counties with younger populations (Column 5), while the effect in counties with older populations is not statistically significant (Column 6).

Despite a more concentrated branch network, consumers in the area have access to a larger number of banking service providers. In Table 2 Panel B, we estimate Specification (2) using data from all lenders that originate loans in a region, regardless of their local branch presence. We find that 3G expansion is associated with a reduction in mortgage market concentration. A 100% increase in 3G coverage reduces mortgage market concentration by 0.024 standard deviations. Moreover, the expansion of 3G enables more lenders to enter and serve a region. As 3G fully covers a region, the number of banks servicing the area increases by 2.7%.

Overall, the findings demonstrate that the expansion of 3G networks prompts less branch-reliant banks to shrink their branch networks and to serve consumers remotely. The increased branch concentration implies that more branch-reliant banks are likely to become more differentiated, but the overall level of competition appears to be intensified by the expansion of less branch-reliant banks.

## 4.2 Individual Bank Analysis

Having illustrated the aggregate impact of 3G expansion, we dig deeper into the effects on individual banks. The bank-level analysis aims to provide a clearer picture of the heterogeneous responses of banks to the expansion of the 3G network.



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We estimate the following specification for different outcome variables:

$$Y_{b,c,t} = \beta 3\text{G Coverage}_{c,t} + \lambda X_{c,t-1} + \mu_{b,s,t} + \nu_{b,c} + \epsilon_{b,c,t}. \tag{3}$$

The key variable of interest, *3G Coverage*$_{c,t}$, and county controls $X_{c,t-1}$ are defined in the same way as in Specification (2). $\mu_{b,c}$ is bank-county fixed effects, allowing us to exploit the time series variation in bank $b$'s decisions in county $c$. $\nu_{b,s,t}$ represents bank-state-year fixed effects, controlling for factors such as shocks to bank $b$'s business activities in state $s$ in year $t$, idiosyncratic exposure to changes in state regulations, and other bank-specific or state-specific shocks. The inclusion of these fixed effects creates a difference-in-difference design that exploits the variation in *a given bank*'s responses across counties that experience various levels of 3G expansion within a state year.

### 4.2.1 Baseline

We investigate various margins of adjustment in individual banks' branching decisions and present the results in Table 3. In column 1, we examine the impact of 3G expansion on the total number of branches that a bank operates across regions. We find that banks operate fewer branches in regions with faster 3G expansion, compared to those with slower 3G expansion within the same state. The magnitude of the impact is 1.3%, which is consistent with the county-level result in Table 2. In column 2, we investigate whether 3G expansion causes a bank's branch network to entirely withdraw from regions with high 3G coverage. To do so, we construct an indicator variable *I(Branch)* that equals 1 if a bank has any branches in a given county. Our result suggests that a bank's branch network is 1.4% less likely to cover a region once the region is fully covered by the 3G network.

It is worth noting that after the financial crisis, the banking industry underwent a process of branch consolidation. Our result captures the contribution of 3G expansion to this process, implying that to some extent, the geographic contraction of a bank's branch network follows 3G's geographic expansion.

### 4.2.2 Heterogeneous Responses Across Banks

We then examine heterogeneity in banks' responses to digital disruption, in terms of both branching decisions and pricing strategies, to gain insights into the underlying transformation in the banking industry. This complements the previously discussed results, which focused on the average effects of digital disruption on bank branching decisions.



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The decision of whether or not to maintain branches may depend on the value that a bank's customers place on them. Banks that focus on customers who value local branches may view branch service as critical to retaining their customers; we refer to these banks as more branch-reliant. Conversely, banks that focus on customers who primarily use digital platforms may require fewer branches; we refer to these banks as less branch-reliant. We acknowledge that a bank's decision to operate as more or less branch-reliant is a strategic choice made historically. Although banks can adapt their business models, these adjustments can be expensive and demand significant resources.

To capture the degree to which banks rely on branches, we measure their branch reliance as the number of branches required to serve every million dollars of deposits in 2007.[17] A lower value indicates that a bank can serve a large amount of deposits without relying heavily on branches, while a higher value indicates greater reliance on branches. Using this measure, we categorize banks as less branch-reliant (*Low BR*) if they fall in the lowest quartile of the branch-reliance index, and as more branch-reliant (*High BR*) otherwise.

Table A4 provides examples of more and less branch-reliant banks based on our measure. For instance, ING Bank, Discover Bank, and E-Trade Bank are typical less branch-reliant banks, while U.S. Bank, Fifth Third Bank, and Charter One Bank are considered more branch-reliant banks. U.S. bank, for instance, had a relatively high BR index in 2007, serving $112 billion deposits with 2,495 branches. We will now investigate whether the impact of 3G expansion on the branching and pricing strategies of these two types of banks is different.

**Heterogeneous Branch Closures** We investigate whether banks with different levels of branch reliance initiate different structural changes following 3G expansions. Intuitively, less branch-reliant banks would benefit the most from 3G networks, and thus, are likely to contract their branch networks after 3G expansion. Table 4 presents the heterogeneous effects of 3G expansion across the two types of banks. We estimate Specification 3 using the Low BR bank sample in Columns 1 and 4, and the High BR bank sample in Columns 2 and 5. For Low BR banks, we find that the full expansion of 3G to a county leads to, on average, a 4% reduction in the number of branches offered in that county and a 2.4% higher probability of closing all branches in that county. These effects are about 2 to 3 times larger than the average effects shown in Table 3. However, High BR banks exhibit much weaker responses. The coefficient estimates of 3G coverage in Columns 2 and 5 are either smaller or statistically insignificant. This divergence in response between the two types of banks is

[17] Figure A1 Panel (a) shows the distribution of the branch-reliance index.



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further supported by the significant coefficient estimates of the interaction term between 3G coverage and the indicator variable for Low BR banks in Columns 3 and 6.

**Diverging Pricing Strategies** We then examine whether banks respond differently in their pricing strategies after 3G expansion as they adjust their branch networks. According to our conceptual framework in Section 2, less branch-reliant banks may reduce prices to attract tech-savvy consumers for two reasons. First, less branch-reliant banks may contract their branch networks following 3G expansion, which could make them less attractive to non-tech savvy consumers who value branch services. Second, the 3G network may attract other less branch-reliant banks to enter the market, increasing local competition. In contrast, as the availability of branches decreases, the remaining branches become more valuable from the perspective of non-tech savvy, branch-captive consumers, allowing more branch-reliant banks to charge higher prices.

We use RateWatch data to analyze bank pricing across product types, including deposit and consumer loan products. Due to sample coverage issues, we estimate a less saturated specifications than Specification (3):[18]

$$
\begin{aligned}
Y_{b,c,t} = {} & \beta 3\text{G Coverage}_{c,t} \times \text{Branch-Reliance}_b + \gamma 3\text{G Coverage}_{c,t} \\
& + \lambda X_{c,t-1} + \mu_{s,t} + \nu_{b,c} + \epsilon_{b,c,t}.
\end{aligned} \tag{4}
$$

3G Coverage$_{c,t}$ and county controls $X_{c,t-1}$ are defined in the same way as in Specification (3). $\mu_{s,t}$ and $\nu_{b,c}$ are state-year fixed effects and bank-county fixed effects, respectively. We interact 3G Coverage$_{c,t}$ with banks' branch reliance index as previously defined. The inclusion of these fixed effects creates a triple-difference design that compares the price changes of more branch-reliant and less branch-reliant banks as the 3G network covers a county.

Panel A of Table 5 presents the deposit pricing results. The outcome variable is deposit spread, defined as the difference between the Fed fund rate and interest rates of 12-month certificate deposits (12MCD) and savings deposits. For both types of deposit products, as 3G expands to a region, more branch-reliant banks offer lower deposit rates (i.e., charge higher rate spreads), while less branch-reliant banks offer higher deposit rates. Specifically, a bank with a branch-to-deposit ratio in line with the average increases its 12MCD spread by 2.5 basis points when 3G fully covers a region. Yet, banks whose branch reliance is 1.8 standard deviation (0.025/0.014) below the average offer reduced 12MCD spreads in response to the

[18] Appendix A.2 discusses the sample coverage issues of RateWatch.



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expansion of 3G coverage. For savings deposits, an average bank in terms of its branch-to-deposit ratio reduces its spread by 3.4 basis points as 3G fully covers a region. In contrast, banks with branch-to-deposit ratio being 1.6 standard deviation (0.034/0.021) above average tend to charge a greater spread with the expansion of 3G coverage.

Panel B of Table 5 presents the loan pricing results, with interest rates on various consumer loan products as outcome variables. Similar to the deposit findings, high BR banks charge higher loan prices compared to low BR banks in response to 3G expansion. Quantitatively, a bank with an average branch-deposit ratio reduces its mortgage spread by 7.3 basis points for a 100% increase in 3G coverage (Column 1). However, banks with 1.3 (0.073/0.056) or more standard deviation higher branch-deposit ratios increase their mortgage spread after 3G expansion. These results hold for auto loans (Column 2) and unsecured credit (Column 3).[19]

Overall, we provide evidence that 3G expansion leads to diverging pricing strategies among banks with different business models. Our findings suggest that as more consumers adopt digital banking channels, banks that rely less on physical branches are better positioned to compete for tech-savvy consumers by offering lower prices. In contrast, more branch-reliant banks face higher costs associated with maintaining a physical presence. Moreover, as fewer banks offer branch services after 3G expansion, their services become more differentiated, allowing them to charge higher markups. Both factors contribute to higher prices charged by more branch-reliant banks.

## 4.3 Identification and Instrument

The previously discussed analysis relies on two primary identification assumptions: first, that the 3G expansion is exogenous and not influenced by other factors that affect banks' branching, pricing, and entry decisions; and second, that 3G coverage is not caused by changes in a bank's behavior. To verify these assumptions, we conducted event studies, discussed in Section 4.1, that showed no pre-trend of branch closure or geographic expansion of banks prior to the sharp increase in 3G expansion, thus alleviating concerns of reverse causality and omitted variables. We also performed bank-level analysis that looked at within-bank's decisions across different regions, eliminating the potential influence of supply-side effects (e.g., the concentration of low-quality banks in areas with high 3G coverage leading

[19] The results of the loan pricing analysis are suggestive, given that changes in borrowers' creditworthiness across banks are not accounted for. One possible confounding factor is that less branch-reliant banks might attract more creditworthy borrowers following the 3G expansion, as less creditworthy borrowers tend to rely more on banks with a local physical presence. In this alternative scenario, the higher loan rates charged by more branch-reliant banks may reflect a greater credit risk. The deposit pricing results, on the other hand, are less susceptible to this concern since adverse selection is not as prevalent in the deposit market.



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to more bank exits in these regions).

Despite the evidence presented, the non-random nature of 3G network expansion means that strong causal inferences cannot be made from the analysis alone. To address any remaining concerns, we use an instrumental variable (IV) approach, leveraging the correlation between lightning strikes and the speed of 3G network expansion (Andersen et al., 2012). Lightning strikes can damage the infrastructure of 3G networks, negatively impacting signal transmission and increasing maintenance costs, resulting in slower adoption and lower supply of 3G networks in areas with more lightning incidents. Therefore, lightning strikes serve as a valid instrument for 3G network expansion speed, allowing us to identify the causal effect of 3G expansion on bank behavior.

Following Guriev et al. (2021) and Manacorda and Tesei (2020), we construct our instrumental variable by multiplying local lightening strike frequency by year. We first compute the average density-weighted lightning strike frequency per square kilometer for each county from 2007 to 2018. We then classify a county as a high-lightning region if its lightning strike frequency exceeds the state median. The *within-state* classification of high-versus low-lightning strike counties alleviate the concern that the estimation is driven by a few states with extreme weather conditions (e.g., Florida). The map of counties classified into high versus low lightning strike regions is presented in Figure 5. Finally, we construct our Bartik instrument by multiplying this indicator variable by $t^2$, where $t$ is the number of years since 2007. In this Bartik instrument, high lightning strike frequency indicator is the cross-sectional accounting identity, while $t^2$ is the time-series accounting identity that captures the non-linear growth of 3G in the aggregate economy (Goldsmith-Pinkham et al., 2020).[20]

### 4.3.1 IV Validity: Discussion and Test

To ensure the validity of our instrument, we next demonstrate its relevance to the speed of the 3G network expansion and its exclusion from other factors that could influence banks' decisions in the local area.

To test the relevance of our instrument, we estimate the first-stage relationship between local lightning strikes and the speed of 3G network expansion and report the results in Table A5. Table A5 confirms that lightning strikes are negatively associated with the speed

[20] The instrument in Manacorda and Tesei (2020) is $\mathbb{1}$[High Lightning] $\times\, t$, and the instrument variable in Guriev et al. (2021) is $\mathbb{1}$[High Lightning] $\times\, t \times \mathbb{1}$[GDP per capita below median] + $\mathbb{1}$[High Lightning] $\times\, t \times \mathbb{1}$[GDP per capita above median]. We show in Table A6 that our results are largely robust to an alternative IV with a linear time trend ($t$ instead of $t^2$) interacted with the lightning strike indicator. As we discuss in Appendix B, the choice of a linear time trend $t$ or a non-linear time trend $t^2$ does not bias the estimation. As F-Statistics in Table A6 are much lower than results with a non-linear trend ($t^2$) in Table 2, we adopt the IV with $t^2$ in the main text.



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of the 3G network expansion, consistent with the existing literature. Specifically, our results indicate that over the 12-year sample period, areas with high lightning activity experience a 3.5% ($0.024 \times 12^2$) slower rate of 3G network expansion compared to areas with low lightning activity within the same state.[21]

The instrument is likely to satisfy the exclusion restriction, as prior studies find that lightning strikes have no impact on local economic growth through channels other than IT diffusion (Andersen et al., 2012). We present two additional pieces of supporting evidence. First, we demonstrate that economic growth conditions, such as trends in GDP growth, population, unemployment rate, the proportion of young people and the number of banks, are similar between regions with high and low lightning strike frequency within a state, as shown in Table A7.[22]

Moreover, we conduct a placebo test by constructing a similar lightning strike IV using data from 2001 to 2006, prior to the existence of 3G technology. The results, reported in Table A8, show that lightning strikes had no statistically significant effect on bank branch, product market entry, or exit decisions during this period. These findings suggest that the effect of lightning strikes on bank decisions after 2007 is likely due to its impact on the 3G network expansion.

### 4.3.2 IV Results and Discussion

We confirm our baseline OLS results in the IV setting and obtain stronger estimated effects. As the 3G network covers the entire county, the total number of branches declines by 30.3% (Table 2 Panel A2, column 1). This results in more concentrated branching markets, with an average increase in the branch concentration measure of 0.39 standard deviation (Table 2 Panel A2, column 4). Moreover, the 3G network expansion leads to an average increase of 49% in the number of bank lenders servicing local mortgage borrowers in a county (Table 2 Panel B, column 4).

Less branch-reliant banks are found to close about 10 times more branches than more branch-reliant banks and are 17.8% more likely to close all branches after the 3G network fully covers a county (Table 4 Panel B). More branch-reliant banks significantly increase

[21] Our estimated effect size is smaller than that reported in Guriev et al. (2021), which is likely due to our focus on the variations in 3G expansion within states in the United States, whereas their study examines variations across the globe.

[22] According to Guriev et al. (2021), lightning strikes hindered the diffusion of information technology, leading to a negative impact on state GDP growth from 1990 to 2007. However, our balance test results differ from their findings for two possible reasons. Firstly, while Guriev et al. (2021) calculates the number of lightning flashes per square kilometer, our measure takes into account local population density, making our results less likely to be affected by differences in growth between rural and urban regions. Secondly, we compare counties within the same state, which may have more similar economic conditions than counties across different states.



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their prices relative to less branch-reliant banks after 3G expansion (Table 5). In the deposit market, rate spreads increase by 2-6 basis points more for banks with one standard deviation higher branch-reliance ratio. In the loan market, loan rates across various consumer loan products increase by 6-40 basis points more for banks with one standard deviation higher branch-reliance ratio .

**Magnitude Discussion** The IV estimates of the effect on branches are larger than the OLS estimates in Tables 2–4 for two possible reasons. First, endogeneity issues may cause the OLS estimates to underestimate the effect. For example, as telecommunication companies tend to more quickly expand 3G services in higher-income areas, banks could find it not optimally to close branches if these areas have more users that value branch services. Although we include time-varying local economic and demographic variables to address this issue, unaddressed biases may remain. As for the effect on pricing strategies, the OLS estimates and the IV estimates in Table are not remarkably different from each other because this endogeneity problem is unlikely to significantly downward bias the pricing strategies.

Second, our IV estimates may only capture the local average treatment effect (LATE) due to heterogeneous effects of 3G expansion on banks' decisions. If the 3G networks have a larger impact on banks' decisions among complier regions (i.e., regions where 3G expansion is constrained by lightning strikes) than non-complier regions, IV estimates are expected to be larger than OLS estimates. For instance, lightning strikes are more likely to constrain 3G expansion in more remote areas that do not benefit from population clustering. It is probable that households and banks in such regions are more responsive to the introduction of 3G networks because the local markets are less competitive.

# 5 Distributional Effect: Reduced-Form Evidence

Having illustrated the effect of 3G expansion on the alteration of bank branching and pricing strategies, we study the resulting distributional effect on consumers. The expansion of less branch-reliant banks is expected to benefit tech-savvy consumers, while non-tech savvy consumers may suffer from reduced access to banking services and a higher risk of financial exclusion due to the reduction in the number of branches and increased costs. In this section, we provide suggestive reduced-form evidence using the FDIC Survey of Consumers Use of Banking and Financial Services data. We then build a structural model in the next section to quantify the distributional effect of digital disruption on consumer surplus.



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## 5.1 Descriptive Statistics about Unbanked Population

Table 1 Panel A summarizes the characteristics of the unbanked or under-banked population, based on the FDIC surveys.[23] On average, compared to banked households, unbanked and under-banked households are younger, have lower incomes, are less educated, and are more likely to be racial minorities. While the proportion of unbanked households has continually decreased, there were still 5.25% of households without any bank account in 2019 and 19.35% of under-banked households who used non-bank transactions or credit services over the past 12 months in 2017 (Figure A2).[24]

## 5.2 Effect of Digital Disruption on Financial Inclusion

We analyze how the expansion of 3G networks affects the unbanked and under-banked rates across tech-savvy and non-tech savvy consumers. We estimate the following specification for different subsamples of consumers:

$$\text{Unbanked}_{i,c,t} = \beta 3\text{G Coverage}_{c,t} + \lambda X_{i,t} + \mu_t + \nu_c + \epsilon_{i,c,t}. \tag{5}$$

*Unbanked* is an indicator for whether the survey participant does not have any bank account or used non-bank service in the past 12 months. The key variable of interest is $3GCoverage_{c,t}$. Since the survey only records information in MSA for each consumer, we aggregate the 3G coverage to the MSA level.[25] The control variables, $X_{i,t}$, include individual family income, ethnicity and education levels. $\mu_t$ and $\nu_c$ are year and MSA fixed effects, respectively.

Table 6 presents the findings by age group. The estimates in column 1 and 2 show that 3G expansion has a differential effect on the unbanked or under-banked rate depending on the age group. The unbanked or under-banked rate for consumers under 55 years of age decreases, though the estimate is not statistically significant, while it increases significantly for consumers above 55 years of age. Since low-income consumers are more likely to be the marginal users of banking services, we then focus our analysis on this group in columns 3 and 4 of. When restricting the sample to consumers with an annual family income of less than \$30k, we find that the impact of 3G on the unbanked or under-banked rate is even more pronounced. Among consumers under 55 years of age, the unbanked or under-banked

[23] In the FDIC survey, unbanked is defined as not having any bank account, while under-banked is defined as using non-bank service in the past 12 months. Non-bank service includes check cashing, money order, remittance, payday loan, rent-to-own service, pawn shop loan, refund anticipation loan, auto title loan, and other types of loans or lines of credit from payday lender, auto title lender, pawn shop, or check cashier.

[24] In 2019, the survey omitted the question regarding the "underbanked."

[25] We find the weighted average of 3G availability, weighted by the population density in each MSA's polygon.



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rate decreases by 30.0% when the 3G network fully covers an MSA (column 3), while for consumers above 55 years of age, it increases by 25.4% (column 4). The differential treatment effect is statistically significant (column 5), and the qualitative results are robust to using an instrumental variable approach (column 6), where 3G expansion is instrumented by lightning strike frequencies.

Appendix C provides further insights into the impact of digital disruption on the cost of credit. However, our analysis is constrained by data limitations, and we can only offer suggestive evidence based on one year of the HMDA data. Nevertheless, we find that counties with higher 3G penetration tend to exhibit a larger interest rate differential between older and younger borrowers, indicating that digital disruption may be affecting the cost of credit in important ways.

Overall, our results suggest that the introduction of 3G networks has a differential impact on financial inclusion, favoring tech-savvy consumers while leaving non-tech savvy consumers behind. This suggests that banks' response to digital disruption plays a crucial role in shaping financial inclusion outcomes. Our findings shed light on a new channel through which technology advancements can lead to under-served populations.

# 6 Distributional Effect: Quantitative Framework

In this section, we develop a structural model to quantify the distributional effect of digital disruption on consumer surplus. Our model accounts for two important factors that are not captured in reduced-form analyses. First, we consider the varying demand systems across the deposit and loan markets due to differences in customer age and preferences. For example, older customers may be more likely to deposit money, while younger customers may be more likely to seek mortgage loans.[26] In addition, our model accounts for the interaction between banks' branching decisions and demand in both markets. As a branch serves both the deposit and loan markets, the value of a branch depends on the total demand in both markets. This allows us to analyze the impact of digital disruption on each market separately while capturing the interdependence of the two markets. The quantitative analysis in this section aims to deepen our understanding of how banks respond to digital disruption and

[26]The extent to which financial services rely on physical branches is an empirical question that likely varies depending on the type of service. For instance, deposit accounts are typically associated with long-term relationships that require frequent interactions, suggesting that these services may rely more heavily on branches. In contrast, borrowing occurs less frequently, but potential borrowers may still value the ability to speak with loan officers and receive assistance with paperwork at a local branch. Ultimately, the degree to which branches are important for different financial services is likely influenced by a range of factors, including customer preferences, banking regulations, and technological advancements.



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how disruptions in the loan market may affect the deposit market and vice versa. By quantifying the distributional effects of these disruptions, we can gain insights into how different consumer groups are affected by changes in the banking sector.

## 6.1 Setup

There are two types of banks: more branch-reliant banks ($T$-type) and less branch-reliant banks ($F$-type). These banks compete in both the deposit and loan markets and are indexed by $j$. We use the superscript $m$ to distinguish between the deposit market ($m = d$) and the loan market ($m = l$). The two types of banks differ in four dimensions: marginal costs of deposit and lending services, marginal costs of operating branches, digital service quality, and cost of entry. Banks make decisions about entry, branching ($b_j$), and pricing ($\{r_j^m\}, m \in \{d, l\}$). Banking services are differentiated, allowing them to extract economic rents. Markups are determined endogenously for each type of bank.

There are two types of consumers: tech savvy and non-tech savvy. The composition of consumer type differs by markets ($\{\mu_y^m, \mu_o^m\}, m \in \{d, l\}$). Tech-savvy and non-tech savvy consumers differ in their preferences about prices, branches, and digital service quality of banking services; their preferences can differ across the two markets. Consumers in the deposit market may not be the same group of consumers in the loan market. In other words, we assume that consumers make saving and borrowing decisions independently. In both markets, consumers are indexed by $i$ and decide to obtain the banking services offered by $J_T$ $T$-type banks and $J_F$ $F$-type banks or their outside options. Individual consumers take the available options as given, while the number of banks of each type is determined endogenously.

### 6.1.1 Demand

In either the deposit or loan market, consumer $i$ decides between becoming banked with $T$-type banks, banked with $F$-type banks, or the outside option, which could include remaining unbanked or using non-bank services. Each option $j$ is characterized by a bundle of price, number of branches, and digital service quality, $\{r_j^m, b_j, d_j^m\}$. $j = 0$ denotes the outside option of consumer $i$. Since the set up of demand is identical across the two markets, we omit the superscript $m$ in this subsection.



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Consumer $i$ derives the following indirect utility from choosing option $j$:[27]

$$u_{ij} = -\alpha_i r_j + f_i(b_j) + g_i(d_j) + \xi_j + \sum_{t \in \{F,T\}} (\zeta_{it}(\lambda_t) I_{j(t)} + \lambda_t \epsilon_{ij(t)}). \tag{6}$$

$\alpha_i$ is the marginal disutility of a price increase for consumer type $i$, which differs by market $m$. $f_i(b_j) = \beta_i b_j$ is the convenience valued by consumer $i$ from having $b_j$ branches in the local region of residence, which differs by market $m$. $g_i(d_j) = \gamma_i d_j$ is the convenience valued by consumer $i$ from having access to digital banking services with quality $d_j$, which differs by market $m$. $\xi_j$ is the *unobserved* characteristic of bank $j$. $\zeta_{it}(\lambda_t)$ is i.i.d. a "nested logit" random taste that differentiates bank type $t$ and the outside option. $I_{j(t)}$ is an indicator for whether bank $j$ is type $t$. $\lambda_t$ characterizes the correlation of utilities that consumer $i$ derives from all options within bank type $t$. The parameter $\lambda_t$ varies between 0 and 1. $\epsilon_{ij(t)}$ is i.i.d. extreme value idiosyncratic shock to consumer $i$'s preference for $t$-type bank $j$.

The error term $\sum_{t \in \{F,T\}} (\zeta_{it} I_{j(t)} + \lambda_t \epsilon_{ij(t)})$ generates the classic nested logit purchase probability for consumer $i$. If $\lambda_t = 1$, then $\zeta_{it}(\lambda_t) \equiv 0$, and the error term collapses to the simple multinomial logit form. A non-zero nest parameter $\lambda_t$ captures the idea that the preference shocks among type-$t$ banks are correlated, with a correlation of $(1 - \lambda_t)$. The utility of the outside good is given by another logit error $\epsilon_{i0}$.

Consumer $i$ chooses bank $j$ of type $t$ if doing so yields the highest indirect utility among all options. That is, $s_{ij} = Pr(u_{ij} > u_{ij'}, \forall j')$, where $s_{ij}$ is the probability of household $i$ choosing option $j$. Integrating over the consumers' idiosyncratic preference shocks, we derive $s_{ij}$ as follows:

$$s_{i,j}(r_j, b_j, d_j) = \frac{A_{i,j}}{Z_{i,t}} \frac{Z_{i,t}^{\lambda_t}}{1 + \sum_{t \in \{T,F\}} Z_{i,t}^{\lambda_t}}, \quad t \in \{T, F\} \tag{7}$$

where $A_{i,j} = \exp(\frac{1}{\lambda_t}(-\alpha_i r_j + \beta_i b_j + \gamma_i d_j + \xi_j))$, and $Z_{i,t} = \sum_{j=1}^{J_t} \exp(\frac{1}{\lambda_t}(-\alpha_i r_j + \beta_i b_j + \gamma_i d_j + \xi_j))$.[28] The probability of household $i$ choosing outside option $j = 0$ is

$$s_{i,0} = \frac{1}{1 + \sum_{t \in \{T,F\}} Z_{i,t}^{\lambda_t}}. \tag{8}$$

Given the total market size $M$ and the share of each type of consumers, $\mu_i$, the total demand

[27] This is a reduced-form way to model the demand curve that captures demand heterogeneity. We discuss in Section 6.3 about various possible micro-foundations of this demand.

[28] See Appendix D for a step-by-step derivation.



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for bank $j$ in market $m$ is

$$D_j(r_j, b_j, d_j) = \sum_{i \in \{y,o\}} \mu_i s_{i,j}(r_j, b_j, d_j)M. \tag{9}$$

### 6.1.2 Supply

Operating in a market entails a fixed entry cost $c_j \in \{c_T, c_F\}$ that differs by bank type. Conditional on serving a market, bank $j$ sets the price of its services in both markets, $\{r_j^d, r_j^l\}$, and decides the number of branches, $b_j$, to maximize their variable profits:

$$\max_{r_j^d, r_j^l, b_j} \underbrace{(r_j^d - c_j^d)D_j^d(r_j^d, b_j, d_j^d)}_{\text{deposit profit}} + \underbrace{(r_j^l - c_j^l)D_j^l(r_j^l, b_j, d_j^l)}_{\text{lending profit}} - \underbrace{\kappa_j b_j}_{\text{branch cost}}, \tag{10}$$

where $D_j^d$ and $D_j^l$ are demand for bank $j$ in the deposit and loan markets, respectively; the last term is the total cost of the operating branches.[29] The first order conditions yield the following pricing and branching strategies for bank $j$:

$$r_j^d = \underbrace{c_j^d}_{\text{marginal cost}} + \underbrace{\Big(-\frac{\partial log(D_j^d)}{\partial r_j^d}\Big)^{-1}}_{\text{markup}} \tag{11}$$

$$r_j^l = \underbrace{c_j^l}_{\text{marginal cost}} + \underbrace{\Big(-\frac{\partial log(D_j^l)}{\partial r_j^l}\Big)^{-1}}_{\text{markup}} \tag{12}$$

$$b_j = \underbrace{\Big(r_j^d - c_j^d\Big)\frac{\partial D_j^d}{\partial b_j}}_{\substack{\text{marginal benefit of branch} \\ \text{in deposit market}}} + \underbrace{\Big(r_j^l - c_j^l\Big)\frac{\partial D_j^l}{\partial b_j}}_{\substack{\text{marginal benefit of branch} \\ \text{in loan market}}}. \tag{13}$$

In either market, bank $j$ determines its pricing strategy as a function of its marginal cost and a standard markup term, given the number of branches. To determine the optimal number of branches, bank $j$ trades off the benefit of having more branches, which leads to greater differentiation and higher markups, against the cost of opening and maintaining branches. Importantly, the benefits of additional branches are not specific to a single market; rather, they impact both markets. Therefore, shocks to consumers' preference for branches in one market can affect banks' branching decisions, which in turn, may impact the other market.

[29]The quadratic cost function is used to derive the interior solution for the number of operating branches.



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The total bank profit, with the optimal decisions $\{r_j^{d*}, r_j^{l*}, b_j^*\}$, net of entry cost $FC_j$ is

$$\pi_j^* = \sum_{m \in \{d,l\}} (r_j^{m*} - c_j^m) D_j^{m*} - \kappa_j b_j^* - FC_j. \tag{14}$$

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

#### 6.1.3 Equilibrium

The equilibrium is the market structure comprising the number of banks of each type, $\{J_T, J_F\}$; the pricing decisions , $\{r_T^d, r_F^d, r_T^l, r_F^l\}$; the branching decisions, $\{b_T, b_F\}$; and the demand, $\{D_T^d, D_F^d, D_T^l, D_F^l\}$, such that

1. Consumers maximize utility, taking market structure, branching, and pricing as given (i.e., Equation (7) 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 (Equations (11)-(13) hold 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 $\pi_j$ and no new bank wants to enter the market (Equation (14) holds true for the marginal bank).

Appendix D derives and presents the equilibrium solution.

### 6.2 Estimation and Calibration

To gain a deeper understanding of the nature of digital disruption, we structurally estimate the model, which also helps to rationalize the reduced-form results. Our estimation will set the stage for the counterfactual analyses that follow.

#### 6.2.1 Sample Construction

Our estimation process begins by obtaining the pre-shock structural parameter values using data from before the digital disruption. We define the pre-shock periods for each MSA as the three years before an annual increase of 50% in 3G coverage. We estimate demand and supply separately for each market, using bank deposit and mortgage lending data from



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2007 to 2018. We aggregate the data to market-consumer type-lender observations, where a market refers to an MSA-year. Within each MSA-year, we consider two binary consumer types, young and old, who have different price sensitivities and preferences for branch or digital services. We construct choice sets by looking at the set of realized deposit taking or loan origination for a given market. We classify banks as more branch-reliant and less branch-reliant, following the definition in Section 4.2.2, where more branch-reliant banks are categorized as $T$-type banks and less branch-reliant banks as $F$-type banks.

We use the FDIC Summary of Deposit to obtain deposit volumes taken by banks from young (old) depositors within MSA-years. Since we only observe deposit volume at the branch level and do not have individual depositors' demographic information, we assume that deposits are sourced from young (old) depositors when the branch is located in a zip code with a median age below (above) the sample median. To find deposits from young (old) depositors, we add the deposit quantity at branches located in zip codes with median ages below (above) sample median. We estimate the proportion of young (old) consumers who opt for outside options by calculating the share of under (above) the corresponding median age defined above in the population that do not have a deposit account in the FDIC Survey of Household Use of Banking and Financial Services.

We estimate loan demand using residential mortgage data because mortgages are a major asset category on bank balance sheets and the mortgage market has undergone significant technological disruption since the financial crisis (Buchak et al., 2018b; Fuster et al., 2019). We use the HMDA to obtain total mortgages originated by each bank type to young and old borrowers within MSA-years. To find loans lent to young (old) borrowers within the MSA-years, we assign the zip-code median age obtained from the Census to each borrower and find the aggregate loan volume lent to borrowers in zip codes with median ages below (above) sample median. For each market-consumer type, we find the proportion of consumers that choose their outside option by grouping all loans originated by non-bank mortgage originators.[30]

On the supply side, we obtain the average deposit rate spread and the average mortgage rate charged by each bank type in each MSA-year using RateWatch. We assume a zero price charged to stay unbanked in the deposit market and use the average 30-year fixed mortgage rate as the price of the outside option in the lending market. We use the FDIC Summary of Deposit to obtain the average number of branches per zip code within MSA-years opened by each bank type, which captures the typical number of branches near a depositor's home.

[30]The outside option in the mortgage market is modeled differently from the deposit market because potential homebuyers searching in the mortgage market are unlikely to choose non-mortgage options — either paying with cash or keep renting.



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In the lending market, we obtain the number of lenders by taking the median number of lenders per zip code within the MSA, following Buchak et al. (2018a). This captures the typical number of loan offerings from each type of lender in a borrower's choice set.

#### 6.2.2 Estimation of Pre-Shock Parameter Values

Our demand estimation follows Berry and Jia (2010), where the optimality conditions for depositors, borrowers, and banks determine the mapping between model parameters and observable quantities, such as market shares, branch counts, deposit and loan rates, and number of banks. We use the generalized method of moments (GMM) to separately estimate the following specification, which is the log difference between Equations (7) and (8), for the deposit market and the loan market:

$$log(s_{ij}) - log(s_{i0}) = -\frac{\alpha_i}{\lambda_t} r_j + \frac{\beta_i}{\lambda_t} b_j + \frac{\gamma_i}{\lambda_t} d_j + \frac{\xi_j}{\lambda_t} + (\lambda_t - 1) log(Z_{i,t}). \tag{15}$$

We need instruments for banks' rates and number of branches to account for the potential endogeneity between banks' pricing and branch decisions and the unobservable demand shocks. In addition, hidden shocks to the aggregate demand for a particular type of bank could bias the estimation of the nested logit parameters $\lambda_t$, which also necessitates the use of appropriate instruments. To this end, we adopt a set of cost shifters, including wages, house prices, and rents, to instrument rates, branches, and the substitution between the $T$-type banks and $F$-type banks, following (Xiao, 2020; Wang et al., 2022). More specifically, we find a bank's exposure to cost shocks in other regions where i has branches, to instruments its decisions in a focal MSA. The rationale is that an increase in operating costs in other regions where a bank has branches could affect its overall cost and, hence, its decisions in a focal MSA. Other regions' economic conditions are unlikely to directly affect consumer demand in the focal MSA. The moment conditions are given by the orthogonality condition between the unobservable demand shocks $\xi_j$ and the cost shifters $z_j$: $E[\xi_j z_j] = 0$.

On the supply side, optimal bank pricing strategies as described in Equations (11) and (12) imply that the marginal costs of deposit-taking and lending are equal to the differences between the observed prices and markups. The markups are calculated according to equation (11) and (12) once we obtain the preference parameters in Equation (15). Using the estimated demand and the marginal costs of deposit-taking and lending, we then find the marginal cost of a branch, $\kappa_j$, by employing banks' optimal branching strategies (13). Lastly, by applying the free-entry condition (14), we obtain the fixed entry costs, $FC_j$.



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#### 6.2.3 Calibration: Digital Disruption

After estimating the parameter values prior to the digital disruption, we then calibrate changes in parameters to match the effects of the digital disruption identified in the reduced-form analysis. We focus on two sets of parameters that are most likely to be influenced by the 3G expansion: the quality of digital service valued by young and old consumers, and the marginal costs of $F$-type and $T$-type banks. As previously discussed, the 3G expansion allowed for the first high-speed mobile network, which significantly improved the digital banking experience through phones. This quality improvement may have altered consumers' preferences for digital services, making them more willing to switch to digital banking channels. Additionally, the cost of providing banking services may have decreased due to the 3G expansion. For example, consumers can now use their mobile devices to find solutions to minor issues, leading to a reduction in the cost of providing customer service.

We calibrate the changes in these two sets of parameters to match the model-predicted moments with the effects of 3G coverage identified in the reduced-form analysis. Specifically, we calibrate 8 parameters related to the digital preferences of old and young consumers in both markets and the marginal costs of both bank types in both markets to match 8 empirical moments. These moments include branch closures of both bank types (Table 4), deposit and loan pricing of both bank types (Table 5), and unbanked rates of both types of consumers (Table 6).

### 6.3 Results and Discussion

Table 7 presents the estimation and calibration results. The top two panels show the estimated pre-shock parameter values. The bottom panel shows the calibrated value changes that reflect how the digital disruption affects the demand and the supply.

The estimated price sensitivities ($\alpha_y$ and $\alpha_o$) suggest that depositors are less price sensitive than borrowers in general, and young consumers are more price-elastic than old consumers in both markets. In the deposit market, the median own-rate elasticity for young depositors is 0.224, but is only 0.047 for old depositors. In the loan market, the median own-rate elasticity for young and old borrowers is 3.419 and 0.783, respectively. The estimates in both markets are close to the estimates in the literature (Egan et al., 2017; Xiao, 2020; DeFusco and Paciorek, 2017; Buchak et al., 2018a). The difference in price sensitivities between young and old consumers could be driven by differences in the banking relationship stickiness, search frictions, and switching costs. For example, old consumers may have a



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higher opportunity cost of searching. Also, old consumers may have longer and more diverse business relationships with their home banks, and thus, may find it costlier to switch banks. The difference in price sensitivities between depositors and borrowers could reflect the difference in their stickiness. Since changing deposit accounts may involve new account opening, transferring funds, and changing automatic payment setups as well as direct deposit setups, depositors may be deterred from switching banks even if they are dissatisfied with the interest rates being offered.[31]

Consistent with the survey results that old consumers are more likely to use branches as the primary method of accessing their bank accounts, the estimated preference for branches is much larger for old consumers ($\beta_o$) than for young consumers ($\beta_y$), in both the deposit and loan markets. The estimated $\gamma_y d_F$ and $\gamma_o d_F$ values suggest that young depositors derive more utility from digital services than old depositors, while the difference across young and old borrowers is insignificant in the pre-shock sample. This is not surprising, given that traditional mortgage origination was barely conducted on digital platforms before the introduction of the 3G networks. It is worth noting that the estimates across the two product markets are not directly comparable because the benchmarks are different. More specifically, the estimated digital service quality is relative to the outside options, which are likely to be different across these two markets (e.g., non-bank mortgage originators may have higher digital service quality than the non-bank options faced by depositors). These benchmark effects are captured by the constant term.

The estimated nested logit parameters ($\lambda_T$ and $\lambda_F$) suggest that borrowers view $F$-type lenders as more substitutable than $T$-type lenders, while depositors view $F$-type banks as less substitutable than $T$-type banks. Overall, banks compete more intensely within each group than across groups due to the nested structure.

On the supply side, the estimated marginal cost of operating branches for $F$-type banks ($\kappa_F$) is higher than that for $T$-type banks ($\kappa_T$). This result is consistent with the idea that traditional banks operate branches more efficiently. For example, traditional banks may enjoy economies of scale in operating branches, paying less rent and salaries to serve one additional branch. As for the marginal cost of deposit taking, the negative estimates indicate that taking extra deposits provides benefits, and these benefits are larger for $F$-type banks.[32] The estimated marginal cost in the loan market suggests that extending an additional dollar of loan is costlier for $F$-type banks than for $T$-type banks (e.g., higher funding cost or higher advertisement cost).

[31] As shown in the literature, depositors are sticky. See, for example, Hanson et al. (2015).

[32] Note that $r^d$ is deposit spread in our estimation, so the cost of issuing the deposit has been deducted. The average deposit spread is around 0.5%, and is negative for more than half of the banks in the sample.



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Finally, we find that the introduction of the 3G networks resulted in several changes to this system. Firstly, the 3G network increases young consumer utility derived from digital service. After the 3G network covered an area, the digital service quality perceived by young borrowers increases by 59% (1.629/2.769) in the loan market and increases by 20% (0.045/0.228) in the deposit market. In contrast, the quality perceived by old consumers decreases by 6% (-0.212/2.790) in the loan market and increases by 9% (0.021/0.236) in the deposit market. It is worth noting that our estimates capture the joint effect of changes in households' preferences and changes in digital service quality. Thus, the results could reflect the improvement in digital service quality or changes in young consumers' preference toward digital services. Moreover, the 3G expansion significantly reduces the marginal cost of lending for $T$-type banks by approximately 21% (0.456/2.148), while the effects on the marginal cost of lending for $F$-type banks and the marginal cost of deposit-taking for both bank types are minor, less than 1%. Overall, our results suggest that the expansion of the 3G network had a more substantial effect on improving the perceived digital service quality than on reducing costs.

## 6.4 Counterfactual Analysis

We use the estimated model to quantify the distributional effect of a digital disruption and analyze how banks' endogenous responses contribute to this effect.

### 6.4.1 Effect of Digital Disruption

We begin by quantifying the distributional effect of digital disruption. According to our calibration, the 3G network mainly improved the digital service quality perceived by young people ($\gamma_y d_F$) and lowered the marginal cost of lending for $F$-type banks ($c_F$). We examine how banks' relative market power and consumer surplus vary as we impose the calibrated changes to digital service quality and marginal costs, while keeping the remaining parameters the same as their pre-shock values.[33] We will use *digital disruption* to refer to this exercise.

Figures 6 presents the results. Panel (a) shows the effects on banks' markups, where markups are defined in Equations 11 and 12. After the digital disruption, the markups charged by $T$-type banks increase, while the markups charged by $F$-type banks decrease. The intuition is as follows. The digital disruption improves the perceived quality of digital services, which gives $F$-type banks an edge. The increased quality should increase $F$-type

[33] We impose the calibrated changes to the eight parameters as listed in Table 7.



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banks' market power and allow them to charge higher markups. However, the digital disruption also reduces the importance of physical branches as a means to attract customers, making it more profitable for more $F$-type banks to enter the market. The increased competition mitigates the impact of the digital disruption on markups, leading to a reduction in the markup charged by $F$-type banks.

The forces that drive $T$-type banks' markups are nuanced. Two primary forces are at play. Firstly, as the improved digital service quality allows $F$-type banks to attract more young consumers, old consumers make up a larger proportion of $T$-type banks' customer base. Consequently, the demand faced by $T$-type banks is less price elastic. Secondly, as branches become less appealing from the perspective of demand, the traditional bank business model becomes less profitable, forcing some $T$-type banks to exit the market. This leaves fewer options for consumers who value traditional banking services.

Overall, these structural changes lead to a market transformation where $T$-type banks specialize in serving non-tech savvy consumers, while $F$-type banks serve more tech-savvy consumers. As a result, both types of banks can effectively price discriminate against their respective target markets.

Panel (b) illustrates the effect on consumer surplus. To obtain the change in consumer surplus, we follow Nevo (2000) to find the dollar equivalent measure of the expected utility from their optimal choices:

$$\Delta \text{Consumer Surplus}_i = \frac{1}{\alpha_i}\Big[\underbrace{\ln\Big(\sum_{j\in T,F}\exp(\frac{1}{\lambda_t}(-\alpha_i r_j^{post} + \beta_i b_j^{post} + (\gamma_i d_j)^{post}))\Big)}_{Post-disruption} - \underbrace{\ln\Big(\sum_{j\in T,F}\exp(\frac{1}{\lambda_t}(-\alpha_i r_j^{pre} + \beta_i b_j^{pre} + (\gamma_i d_j)^{post}))\Big)}_{Pre-disruption}\Big]. \tag{16}$$

$\Delta Consumer\, Surplus_i$ measures how consumer $i$'s surplus changes after the digital disruption. We remove the direct effect of changes in consumer utility function ($\Delta\gamma_i d_F$) from the calculation of changes in consumer surplus and unbanked rate. This ensures that our measured change is solely from the banks' endogenous responses to the digital disruption.

Panel (b) shows that old consumers are strictly worse off after a digital disruption, especially in the deposit market, while young consumers benefit from improved digital services. Notably, we assume that consumer preferences remain the same in calculating the changes in consumer surplus, so the welfare changes are entirely attributed to banks' endogenous



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responses. Quantitatively, as shown in Table 8, young houselds' unbanked rate declines by about 0.45%, corresponding to a 7.3% decline from the average pre-shock unbanked rate of 6.2%. Young depositors experience a 0.95 cent improvement in surplus for every dollar saved. In contrast, the unbanked rate of old households increases by 0.15%, a 6.3% rise from the pre-shock average unbanked rate. In total, old depositors' surplus declines considerably by 7.06 cents for every dollar saved.

In the loan market, digital disruption leads to a reduction in credit availability for both old and young borrowers from banks. About 1.0% (0.17%) more old borrowers (young borrowers) end up using non-bank credit. Since both young and old borrowers value branch services in the loan market, their surplus decreases as a result of branch closures. However, young borrowers receive some offsetting benefit from the relatively cheap loans offered by $F$-type lenders. On the other hand, old borrowers who depend on traditional branch-based services offered by $T$-type banks experience a larger reduction in total surplus.

### 6.4.2 Shock Spillovers

We next consider two counterfactuals to better understand how digital disruption in one market affects the other market through the banks' optimal responses to the changing environment. In the first counterfactual, we consider the case where digital disruption only occurs in the deposit market. In the second counterfactual, we assume that digital disruption only happens in the loan market. We find the effects of digital disruption in both cases and compare them to the baseline case in Section 6.4.1.

Figure 7 presents the results. Panel (a) shows that if a digital disruption were to occur only in the deposit market, old depositors would not be worse off. Intuitively, the depositor pool has a relatively larger share of old consumers, and the same amount of digital improvement and cost reduction of banks may not be large enough to affect bank entry and exit in the market. In contrast, the borrower pool has more young consumers who value digital services. When the loan market experiences digital disruption, traditional banks exit the market and $F$-type banks close branches. As shown in Panel (b), these forces together make old depositors worse off when a digital disruption shocks the loan market.

Quantitatively, as shown in Table 8, disruption in the deposit market leads to a 0.034% decline in the old depositors' unbanked rate. The difference in the depositor's surplus change between the baseline case and counterfactual 1 illustrates how a digital disruption occurring in the loan market spills over to the deposit market. Specifically, the spillover of the loan market disruption causes a 0.18% (0.148%-(-0.034%)) rise in the old depositors' unbanked



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rate, when compared to the 0.148% increase in the unbanked rate in the baseline case. In total, the old depositors' surplus declines by 7.86 (-7.058-0.8) cents per dollar of deposits due to the loan market disruption. Overall, the results suggest that a technology shock in the lending market, which disproportionately affects younger generations, can result in negative spillover effects to older generations in the deposit market. This underscores the need to consider the intergenerational impacts of technology adoption and innovation.

#### 6.4.3 Branching Regulation

Lastly, we consider policies that could alleviate the distributional impact as the banking sector undergoes digital transformation. To find the most effective policies, we need to first disentangle how banks' responses resulted in the distributional effect. Specifically, we compare the effects of the calibrated digital disruption in two scenarios: (1) when banks can optimally adjust their rates in response to digital disruption, and (2) when banks can optimally adjust both rates and branches. In both scenarios, we allow for free entry and exit. The comparison of these two cases will inform us about the relative contribution of bank pricing and branching decisions to the distributional effect.

Figure 8 presents the effects on consumer surplus across these scenarios. Panel (a) shows the effects on depositors, and Panel (b) shows the effects on borrowers. The results indicate that bank branch adjustments are the primary driver of the distributional effect in both markets. When banks can only adjust prices, old borrowers' surplus decreases by 0.895 cents per dollar of loan demand, which is less than one-third of the total effect in the baseline case where banks can adjust both rates and branches (Table 8). In other words, bank branch adjustments account for more than two-thirds of the distributional effect in the loan market. In the deposit market, bank branch adjustments contribute to nearly all of the reduction in the old depositors' surplus.

The result is not solely driven by a large estimated $\beta$ in the consumers' utility function. Instead, we demonstrate that the product of $\beta$ and the banks' optimal branch adjustment (i.e., $\beta\Delta b$) explains a significant portion of the consumer surplus changes. Since banks take into account consumers' valuation of branches (measured by $\beta$) when responding to digital disruption, a larger $\beta$ does not necessarily mean fewer branch closures. Thus, a high $\beta$ alone does not necessarily result in a reduced impact of bank branch adjustments on the distributional effect.

Given the importance of bank branch adjustments for the distributional effect, we analyze the effectiveness of regulations that restrict branch closures. We model it as caps on the



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percentage of branches that are allowed to be shut down and compare the effect of digital disruption on consumer surplus with and without such a regulation.

Figure 9 shows changes in consumer surplus by consumer type and total consumer surplus under different scenarios. When the optimal branch adjustment of banks does not result in branch closures beyond the regulatory threshold, the digital disruption effect on consumer surplus is the same as the baseline without regulations. However, as the regulation becomes binding, banks increase prices to cover branch costs, and old consumers benefit the most due to their strong preference for branches and low price sensitivity. Young depositors' surplus may decrease slightly since they are more price-sensitive and do not value branches as much, while young borrowers' surplus may increase as the regulation tightens. Despite the decrease in young depositors' surplus, the increase in old consumers' surplus dominates, resulting in an overall increase in total surplus as stricter branch closure regulations are imposed.

# 7 Conclusion and Discussion

In this paper, we study the impact of digital disruption on bank competition and its distributional effects on heterogeneous consumers. Our results show that banks with a lower reliance on branches tend to close costly branches and expand services to new regions after digital disruption, leading to an increase in the number of banks serving each county but a more concentrated branch network. In contrast, banks that rely heavily on branches target non-tech savvy customers and exploit their market power to charge higher prices, resulting in limited branch options and higher markups for these consumers. This changing landscape has important implications for different consumer groups. Tech-savvy customers benefit from more intense competition and lower banking costs, while non-tech savvy customers who value branch services face the risk of financial exclusion due to limited branch options and higher markups.

We highlight that the benefit of digital disruption may come at a cost to non-tech savvy consumers, which receives less attention in the current discussion of how technology affects the economy. We also bring in a new perspective of diverging customer preferences and product differentiation in analyzing how technology affects bank competition, which is absent in the current discussion. Our paper sheds light on the consequences of digital disruption in terms of financial inclusion and potential price discrimination. By unraveling the heterogeneous consumers and banks, we hope this paper can provoke new insights into the interaction between technology and financial intermediaries and how to balance the benefits and costs of digital disruption to ensure that financial services remain accessible to all consumers.



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## **Table 1** Summary Statistics

Panel A1 presents summary statistics for county-level data from 2007 to 2018. The first three branch-related variables are constructed using the FDIC Summary of Deposit (SOD) data. The next two lender-related variables are constructed using the Home Mortgage Disclosure Act (HMDA) data. 3G Coverage is constructed using the digital maps provided by Collins Bartholomew's Mobile Coverage Explorer. Panel A2 presents summary statistics for bank-county level data. Branch to Deposit Ratio is constructed using the FDIC SOD data in 2007. Number of Branches is the number of branches opened by a bank in a county, constructed using the SOD data from 2007 to 2018. Rate spreads on different financial products are constructed using the RateWatch data from 2007 to 2018. Money Market 25K rate spread is calculated as the Fed fund rate minus the interest rate on money market deposit accounts with an account size of $25,000. Mortgage, Auto Loan, and Unsecured Credit rate spreads are calculated as loan rates minus the Fed fund rate. For each loan category, we include several loan types with more populated pricing data. Appendix A provides details about these loan types. Panel C presents the demographic characteristics of different groups classified based on their responses in The FDIC Survey of Household Use of Banking and Financial Services, conducted biennially from 2009 to 2019. The first three columns are classified based on people' bank account ownership status. The unbanked (banked) samples include individuals without (with) a bank account. The underbanked sample is a subset of the banked sample, including individuals who have used non-bank financial services in the past 12 months. The last four columns are restricted to banked population and are classified based on their most common way to access bank account. Data for this sample is available from 2013 to 2019. We report the average age, annual income, ratio of individuals with a college education, and the ratio of the white population for each population category. Numbers in parentheses are standard deviations. We remove outliers by winsorizing all variables in Panel A2 and B at the 1% and 99% levels.

**Panel A: County and Bank-County Samples**

| | (1) Count | (2) Mean | (3) Stdev | (4) P5 | (5) P25 | (6) Median | (7) P75 | (8) P95 |
|---|---|---|---|---|---|---|---|---|
| **Panel A1: County-Level Observations** | | | | | | | | |
| Number of Branches | 36,744 | 29.1 | 74.3 | 2 | 5 | 10 | 22 | 119 |
| Branch Per Bank | 36,646 | 2.2 | 1.6 | 1.0 | 1.2 | 1.7 | 2.5 | 5.4 |
| Branch Concentration | 36,646 | 2621 | 2046 | 796 | 1289 | 2000 | 3333 | 5557 |
| Number of Lenders | 33,605 | 67.9 | 75.1 | 7 | 21 | 43 | 84 | 226 |
| Mortgage Market HHI | 33,605 | 1138 | 1061 | 318 | 544 | 831 | 1335 | 2944 |
| 3G Coverage (%) | 36,744 | 57.7 | 43.4 | 0.0 | 0.2 | 82.1 | 98.7 | 100.0 |
| **Panel A2: Bank-County Level Observations** | | | | | | | | |
| Branch to Deposit Ratio (%) | 8,588 | 3.7 | 3.4 | 0.8 | 1.8 | 2.8 | 4.3 | 8.9 |
| Number of Branches | 519,804 | 2.1 | 5.7 | 0.0 | 0.0 | 1.0 | 2.0 | 8.0 |
| Rate Spread (%) | | | | | | | | |
| Money Market 25K | 327,812 | 0.4 | 1.1 | -0.8 | -0.2 | 0.0 | 0.8 | 2.9 |
| Mortgages | 99,856 | 3.5 | 1.2 | 1.4 | 2.9 | 3.6 | 4.4 | 5.4 |
| Auto Loans | 981,291 | 4.7 | 1.8 | 2.0 | 3.2 | 4.6 | 6.1 | 7.9 |
| Unsecured Credit | 144,786 | 10.6 | 3.4 | 5.6 | 8.1 | 10.0 | 12.7 | 17.6 |

**Panel B: FDIC Survey**

| | Bank Account Ownership Status | | | Most Common Way to Access Account | | | |
|---|---|---|---|---|---|---|---|
| | (1) Unbanked | (2) Underbanked | (3) Banked | (4) Branch | (5) Online | (6) Mobile | (7) Other |
| Aggregate Share (2009-2019 Average) | 6.93% | 20.58% | 93.06% | 23.81% | 33.64% | 17.70% | 24.86% |
| **Demographics Information** | | | | | | | |
| Age | 43.8 | 45.5 | 49.9 | 57.5 | 49.2 | 39.7 | 51.3 |
| | (15.2) | (15.0) | (15.4) | (14.3) | (14.5) | (13.2) | (15.3) |
| Income | 21809 | 48263 | 59950 | 48591 | 73097 | 66359 | 54219 |
| | (18481) | (31984) | (33882) | (32241) | (31216) | (32586) | (33392) |
| College education | 27.3% | 57.7% | 67.8% | 53.7% | 82.7% | 78.5% | 61.2% |
| | (44.6%) | (49.4%) | (46.7%) | (49.9%) | (37.8%) | (41.1%) | (48.7%) |
| White | 25.8% | 48.7% | 67.1% | 64.5% | 74.5% | 60.3% | 60.4% |
| | (43.8%) | (50.0%) | (47.0%) | (47.8%) | (43.6%) | (48.9%) | (48.9%) |



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**Table 2** 3G and Bank Structural Changes: County-Level Evidence

This table presents county-level regression results about the effects of 3G expansion on the branch networks (Panel A) and loan market concentration (Panel B) in a county. Panel A uses the Summary of Deposit (SOD) data. A1 presents the OLS results. A2 presents the 2SLS results. In both sub-panels, the outcome variable is the logarithm of total number of branches in columns 1-3 and branch concentration in columns 4-6. Branch concentration is calculated as $\sum_j (\frac{Branch_j}{\sum_j Branch_j})^2$, standardized to have a unit variance. Columns 1 and 4 use the full sample. Columns 2 and 5 (3 and 6) use the subsample of young (old) counties. Old counties are defined as counties with the share of below-age 55 population in the bottom quartile, and young counties otherwise. Panel B uses the Home Mortgage Disclosure Act (HMDA) data and restricts to all originated home purchase loans. Columns 1-2 present OLS results. Columns 3-4 present 2SLS results. The outcome variable in columns 1 and 3 is county-level mortgage market HHI index, constructed using market shares of all loans originated to borrowers in a given county. We standardize the outcome variable to have a unit variance. The outcome variable in columns 2 and 4 is the logarithm of number of lenders originating at least one loan in a given county in a given year. In both panels, the variable of interest is 3G Coverage, which is calculated as the proportion of population with access to 3G networks in a county in a year. County controls are lagged by one year, including the log of income per capita, the log of county GDP, the log of the total population, the log of the number of banks, the share of the county population that is below age 55, and the share of the population that is White. Standard errors are clustered at the state-year level. Numbers in parentheses are standard errors. $^{*}$, $^{**}$, $^{***}$ represent statistical significance at 10%, 5% and 1% level, respectively.

Panel A: Branch Network Change

| | Log(1+Branch) | | | Branch Concentration | | |
|---|---|---|---|---|---|---|
| | (1) Full Sample | (2) Young County | (3) Old County | (4) Full Sample | (5) Young County | (6) Old County |
| **A1: OLS** | | | | | | |
| 3G Coverage | -0.014*** | -0.014*** | -0.006 | 0.017*** | 0.014*** | 0.012 |
| | (0.003) | (0.003) | (0.006) | (0.003) | (0.003) | (0.010) |
| Adjusted $R^2$ | 0.998 | 0.998 | 0.996 | 0.973 | 0.976 | 0.975 |
| **A2: 2SLS** | | | | | | |
| 3G $\widehat{Coverage}$ | -0.303** | -0.312** | -0.084 | 0.392** | 0.424** | 0.048 |
| | (0.121) | (0.128) | (0.120) | (0.183) | (0.206) | (0.211) |
| County Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| County FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| State-Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 36,744 | 27,414 | 9,085 | 36,646 | 27,360 | 9,040 |
| Cragg-Donald Wald F-stats | 35.590 | 25.741 | 27.314 | 34.577 | 24.986 | 27.006 |

Panel B: Financial Product Market Competition

| | OLS | | 2SLS | |
|---|---|---|---|---|
| | (1) Mortgage HHI | (2) Log(1+Lenders) | (3) Mortgage HHI | (4) Log(1+Lenders) |
| 3G Coverage | -0.024* | 0.027*** | 0.026 | 0.493* |
| | (0.013) | (0.006) | (0.501) | (0.273) |
| County Controls | ✓ | ✓ | ✓ | ✓ |
| County FE | ✓ | ✓ | ✓ | ✓ |
| State-Year FE | ✓ | ✓ | ✓ | ✓ |
| Adjusted $R^2$ | 0.771 | 0.983 | - | - |
| Observations | 33,605 | 33,605 | 33,605 | 33,605 |
| Cragg-Donald Wald F-stats | - | - | 24.644 | 24.644 |



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**Table 3** 3G and Bank Structural Changes: Bank Level Evidence

This table presents bank-level regression results about the effects of 3G expansion of banks' branching decisions. The underlying sample contains observations at bank-county-year level. To analyze whether a bank's branching network expands or exits from a given county, we construct a balanced bank-county sample that contains all counties that a bank's branching network ever appears over our sample period, which is used in all columns. Columns 1-2 report OLS results. Columns 3-4 report IV results. The outcome variable in columns 1 and 3 is the logarithm of the total number of branches opened by a bank in a given county in a year. The outcome variable in columns 2 and 4 is an indicator of whether a bank has at least one branch in a given county in a year. In all columns, the variable of interest is 3G coverage, which is calculated as the proportion of the population with access to 3G networks in a county in a year. County controls are lagged by one year, including the log of income per capita, the log of county GDP, the log of the total population, the log of the number of banks, the share of the county population that is below age 55, and the share of the population that is White. Standard errors are clustered at the state-year level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

| | OLS | | 2SLS | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Log(1+Branch) | I(Branch) | Log(1+Branch) | I(Branch) |
| 3G Coverage | -0.013*** | -0.014*** | -0.393** | -0.314* |
| | (0.003) | (0.003) | (0.198) | (0.161) |
| Adjusted $R^2$ | 0.894 | 0.843 | - | - |
| Observations | 458,976 | 459,000 | 458,976 | 459,000 |
| County Controls | ✓ | ✓ | ✓ | ✓ |
| Bank-County FE | ✓ | ✓ | ✓ | ✓ |
| Bank-State-Year FE | ✓ | ✓ | ✓ | ✓ |
| Cragg-Donald Wald F-stats | - | - | 268.858 | 268.920 |



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**Table 4** Heterogeneous Effects of 3G Coverage across Banks: Branch Networks

This table presents bank-level regression results about the heterogeneous effects of 3G expansion of banks' branching decisions across banks. The underlying sample contains observations at bank-county-year level. To analyze whether a bank's branching network expands or exits from a given county, we construct a balanced bank-county sample that contains all counties that a bank's branching network ever appears over our sample period, which is used in all columns. Panel A reports the OLS results. Panel B reports the IV results. The outcome variable in the first three columns is the logarithm of the total number of branches opened by a bank in a given county in a year. The outcome variable in the last three columns is an indicator of whether a bank has at least one branch in a given county in a year. Columns 1 and 4 use the sub-sample of less branch-reliant banks, labeled as *Low BR* banks. Columns 2 and 5 use the sub-sample of more branch-reliant banks, labeled as *High BR* banks. Banks are classified as Low BR or High BR based on their branch-reliance indices, defined at bank-level as the number of branches needed to serve every million of deposits in 2007. Low BR sample includes banks in the lowest quartile ranked by their branch-reliance indices. High BR sample includes banks in the top three quartiles. Columns 3 and 6 use the full sample of banks. In all columns, the variable of interest is 3G coverage, which is calculated as the proportion of the population with access to 3G networks in a county in a year. County controls are lagged by one year, including the log of income per capita, the log of county GDP, the log of the total population, the log of the number of banks, the share of the county population that is below age 55, and the share of the population that is White. Standard errors are clustered at the state-year level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

| | Log(1+Branch) | | | I(Branch) | | |
|---|---|---|---|---|---|---|
| | (1) Low BR Bank | (2) High BR Bank | (3) Full Sample | (4) Low BR Bank | (5) High BR Bank | (6) Full Sample |
| Panel A: OLS | | | | | | |
| 3G Coverage | -0.040*** | -0.005 | -0.005 | -0.024*** | -0.011*** | -0.011*** |
| | (0.009) | (0.004) | (0.004) | (0.006) | (0.003) | (0.003) |
| 3G Coverage×Low BR Bank | | | -0.035*** | | | -0.014** |
| | | | (0.010) | | | (0.006) |
| Adjusted $R^2$ | 0.911 | 0.883 | 0.894 | 0.862 | 0.837 | 0.843 |
| Panel B: 2SLS | | | | | | |
| 3G $\widehat{\text{Coverage}}$ | -1.701*** | -0.165 | -0.165 | -0.471 | -0.292** | -0.292** |
| | (0.468) | (0.145) | (0.145) | (0.406) | (0.121) | (0.121) |
| 3G $\widehat{\text{Coverage}}$×Low BR Bank | | | -1.536*** | | | -0.178 |
| | | | (0.489) | | | (0.423) |
| County Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Bank-County FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Bank-State-Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 121,104 | 398,700 | 519,804 | 121,104 | 398,724 | 519,828 |
| Cragg-Donald Wald F-stats | 26.626 | 247.572 | 56.744 | 26.626 | 247.636 | 56.747 |



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## **Table 5** Heterogeneous Effects of 3G Coverage across Banks: Pricing

This table presents bank-level regression results about the heterogeneous effects of 3G expansion of banks' pricing decisions across banks. The underlying sample contains observations at bank-county-quarter-product type level. Panel A reports results about deposit pricing. Panel B reports results about loan pricing across consumer loan categories. In Panel A, the outcome variable is deposit spread, calculated as the Fed fund rate minus the interest rate on 12-month certificated deposit accounts with an account size of $25,000 (12MCD25K) and saving accounts with an account size of $2,500 (SAV2.5K). Columns 1-2 report OLS results, and columns 3-4 report 2SLS results. In Panel B, the outcome variables are loan spreads, calculated as the interest rate on various consumer loan products minus the Fed fund rate. The outcome variable in columns 1 and 4 is rate spread on mortgage products, in columns 2 and 5 is rate spread on auto loans, and in columns 3 and 6 is rate spread on unsecured credit. Columns 1-3 report OLS results, and columns 4-6 report 2SLS results. In both panels, "Branch-Reliance" is defined at bank-level as the number of branches needed to serve every million of deposits in 2007. The index is standardized to have a unit variance. The variables of interest are 3G coverage, which is calculated as the proportion of the population with access to 3G networks in a county in a year, and its interaction with Branch-Reliance. County controls are lagged by one year, including the log of income per capita, the log of county GDP, the log of the total population, the log of the number of banks, the share of the county population that is below age 55, and the share of the population that is White. Standard errors are clustered at the state-year level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

**Panel A: Deposit Products**

| | OLS | | 2SLS | |
|---|---|---|---|---|
| | (1) 12MCD25K | (2) SAV2.5K | (3) 12MCD25K | (4) SAV2.5K |
| 3G Coverage | 0.025*** | -0.034*** | 0.461*** | 0.040 |
| | (0.006) | (0.005) | (0.131) | (0.059) |
| 3G Coverage×Branch-Reliance | 0.014*** | 0.021*** | 0.065*** | 0.019*** |
| | (0.003) | (0.003) | (0.008) | (0.004) |
| County Controls | ✓ | ✓ | ✓ | ✓ |
| Bank-County FE | ✓ | ✓ | ✓ | ✓ |
| State-Quarter FE | ✓ | ✓ | ✓ | ✓ |
| Adjusted $R^2$ | 0.918 | 0.981 | - | - |
| Observations | 342,625 | 348,403 | 342,625 | 348,403 |
| Cragg-Donald Wald F-stats | - | - | 490.813 | 496.015 |

**Panel B: Loan Products**

| | OLS | | | 2SLS | | |
|---|---|---|---|---|---|---|
| | (1) Mortgage | (2) Auto | (3) Unsecured Credit | (4) Mortgage | (5) Auto | (6) Unsecured Credit |
| 3G Coverage | -0.073*** | -0.167*** | -0.358*** | -0.079 | 0.468 | -1.745 |
| | (0.018) | (0.021) | (0.052) | (0.174) | (0.311) | (1.072) |
| 3G Coverage×Branch-Reliance | 0.056*** | 0.138*** | 0.272*** | 0.099*** | 0.056** | 0.397*** |
| | (0.010) | (0.011) | (0.029) | (0.028) | (0.027) | (0.089) |
| County Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Bank-County FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| State-Quarter FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Adjusted $R^2$ | 0.891 | 0.825 | 0.728 | - | - | - |
| Observations | 99,712 | 981,289 | 144,352 | 99,712 | 981,289 | 144,352 |
| Cragg-Donald Wald F-stats | - | - | - | 215.009 | 1230.876 | 124.428 |



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**Table 6** 3G and Financial Inclusion: Survey Evidence

This table presents the results of the effect of 3G coverage on consumers' access to banking services, using the FDIC Survey of Consumer Use of Banking and Financial Services data from 2009 to 2017. The underlying sample contains observations at individual level above 25 years old. The outcome variable, Unbank or Underbank, is 1 if the interviewed households do not have a bank account or have used nonbank transactions and credit services in the past 12 months. The key variable of interest is 3G coverage, which is calculated as the proportion of the population with access to 3G networks in an MSA region in a year. Columns 1-5 report OLS results, and column 6 reports 2SLS results. Columns 1 and 2 use a sub-sample of households with less than 55 years of age in column 1 and more than 55 years of age in column 2. Columns 3 and 4 further narrow the sample to households with an annual income of less than 30k. Finally, columns 5 and 6 use the full sample of households. Controls include individual family income, ethnicity, and education levels. The observations are weighted to account for non-response and under-coverage. Numbers in parentheses are standard errors. Standard errors are clustered at the state-year level. $^{*}$, $^{**}$, $^{***}$ represent statistical significance at 10%, 5% and 1% level, respectively.

**Unbanked or Under-banked**

| | OLS | | | | | 2SLS |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Age<55 | Age≥55 | Age<55& Income≤30k | Age≥55 & Income≤ 30k | Full Sample | Full Sample |
| 3G Coverage | -0.167 | 0.119* | -0.300* | 0.254** | 0.111 | 1.556 |
| | (0.113) | (0.072) | (0.168) | (0.114) | (0.072) | (1.721) |
| 3G Coverage $\times \mathbb{1}$(Age<55) | | | | | -0.253** | -1.476** |
| | | | | | (0.105) | (0.619) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| MSA FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Adjusted $R^2$ | 0.218 | 0.124 | 0.172 | 0.137 | 0.190 | - |
| Observations | 57,336 | 45,218 | 23,838 | 24,047 | 102,554 | 102,554 |
| Cragg-Donald Wald F-stats | | | | | | 147.218 |
| Sample Average | 0.321 | 0.199 | 0.497 | 0.257 | 0.270 | 0.270 |



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**Table 7** Estimated Parameters for the Structural Model

This table presents the estimates of the structural model. The parameters in the first panel represent the demand estimates of Equation (15), which are estimated using three-year bank-county level data that includes the year when a county's 3G coverage increase by more than 50% from the previous year. The demand parameters are estimated using the GMM method with banks' cost shifters as instruments, and the standard errors are reported in parentheses. Using the estimated demand parameters, we calculate the supply estimates for each bank based on Equations (11) to (14) using the pre-shock sample. The average of these supply estimates across banks is reported, along with the standard errors in parentheses. Panel C report calibrated changes in parameters to match the effects of the digital disruption identified in the reduced-form analysis. The matched 8 empirical moments include branch closures of both bank types (Table 4), deposit and loan pricing of both bank types (Table 5), and unbanked rates of both types of consumers (Table 6).

| Parameter | Description | Value: Lending | Value: Deposit |
|---|---|---|---|
| $\alpha_o$ | price sensitivity of old consumers | 0.121<br>(0.221) | 0.031<br>(0.015) |
| $\alpha_y$ | price sensitivity of young consumers | 0.523<br>(0.232) | 0.140<br>(0.018) |
| $\beta_o$ | old consumer's preference for branches | 3.386<br>(0.790) | 3.852<br>(0.484) |
| $\beta_y$ | young consumer's preference for branches | 2.414<br>(0.740) | -2.918<br>(0.472) |
| $\gamma_o d_F$ | digital service quality perceived by old consumers | 2.790<br>(0.423) | -0.236<br>(0.160) |
| $\gamma_y d_F$ | digital service quality perceived by young consumers | 2.769<br>(0.440) | 0.228<br>(0.171) |
| $\lambda_F$ | nested logit in-group correlation among F-banks | 0.128<br>(0.155) | 0.604<br>(0.053) |
| $\lambda_T$ | nested logit in-group correlation among T-banks | 1.000<br>(0.109) | 0.355<br>(0.066) |
| Constant | | -2.878<br>(0.255) | 0.746<br>(0.213) |
| $c_T$ | marginal cost of T-banks | 2.148<br>(0.083) | -5.648<br>(0.094) |
| $c_F$ | marginal cost of F-banks | 5.448<br>(0.045) | -9.381<br>(0.164) |
| $\kappa_T$ | branching cost of T-banks (per intermediated dollar) | 0.550<br>( 0.057) | |
| $\kappa_F$ | branching cost of F-banks (per intermediated dollar) | 0.802<br>0.095 | |
| $FC_T$ | fixed cost of T-banks (per intermediated dollar) | 0.032<br>(0.004) | |
| $FC_F$ | fixed cost of F-banks (per intermediated dollar) | 0.117<br>(0.018) | |
| **Digital Disruption** | | | |
| $\Delta\gamma_o d_F$ | changes in digital service quality by old consumers | -0.212 | 0.021 |
| $\Delta\gamma_y d_F$ | changes in digital service quality by young consumers | 1.619 | 0.045 |
| $\Delta c_T$ | changes in marginal cost of T-banks | -0.456 | -0.081 |
| $\Delta c_F$ | changes in marginal cost of F-banks | -0.024 | 0.028 |



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**Table 8** Quantifying the Effects of Digital Disruption

This table analyzes the impact of digital disruption on consumers' use of banking services and consumer surplus. We measure the impact by applying the calibrated changes to digital service quality and marginal costs in Table 7 panel C, while keeping all other parameters the same as their pre-shock values in Table 7 panels A and B. We remove the direct effect of changes in consumer utility function ($\Delta\gamma_i d_F$) from the calculation of changes in consumer surplus and unbanked rate. This ensures that our measured change is solely from the banks' endogenous responses to the digital disruption. ΔUnbank rate is the change in the share of depositors choosing the outside option after the digital disruption. ΔNon-bank Credit is the change in the share of borrowers choosing the outside option after the digital disruption. The change in depositors' or borrowers' surplus (ΔConsumer Surplus$_i$) is defined in Equation (16). In the top panel (Baseline), we assume calibrated $\gamma_y d_F$, $\gamma_o d_F$, $c_F$, and $c_T$ in both markets change after the digital disruption. In the middle two panels (counterfactuals 1 and 2), we assume only the deposit market or the loan market parameters change. In the bottom panel (counterfactual 3), we assume banks do not change their branches after the digital disruption.

| | ΔUnbank Rate | ΔNon-Bank Credit | ΔDepositor Surplus (per Dollar) | ΔBorrower Surplus (per Dollar) |
|---|---|---|---|---|
| **Baseline: Both Markets Experience Digital Disruption** | | | | |
| Young | -0.449% | 0.165% | 0.952 cents | -0.110 cents |
| Old | 0.148% | 1.021% | -7.058 cents | -3.522 cents |
| **Counterfactual 1: Only Deposit Market Experiences Digital Disruption** | | | | |
| Young | 0.060% | -0.048% | -0.111 cents | 0.163 cents |
| Old | -0.034% | -0.073% | 0.800 cents | 1.013 cents |
| **Counterfactual 2: Only Lending Market Experiences Digital Disruption** | | | | |
| Young | -0.466% | 0.172% | 0.951 cents | -0.134 cents |
| Old | 0.160% | 1.052% | -7.546 cents | -3.664 cents |
| **Counterfactual 3: Banks Respond by Changing Price Only** | | | | |
| Young | 0.506% | -0.001% | -0.988 cents | 0.186 cents |
| Old | 0.184% | 0.214% | -2.862 cents | -0.895 cents |



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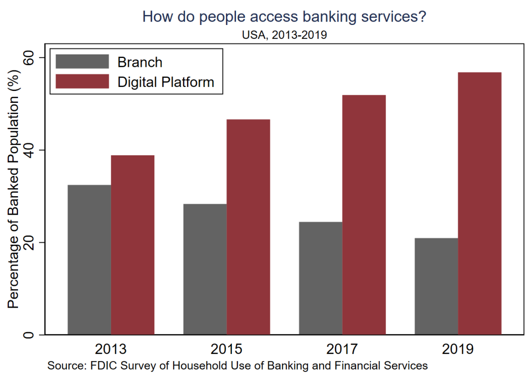
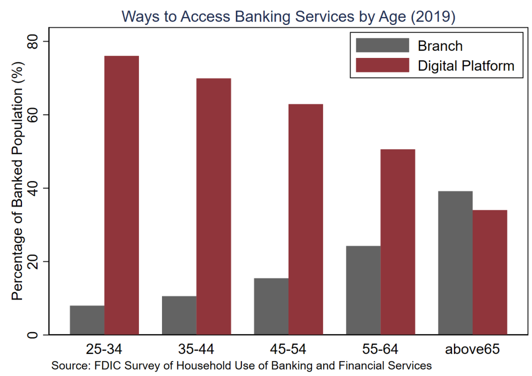
**Figure 1.** Change of Ways to Access Banking Services

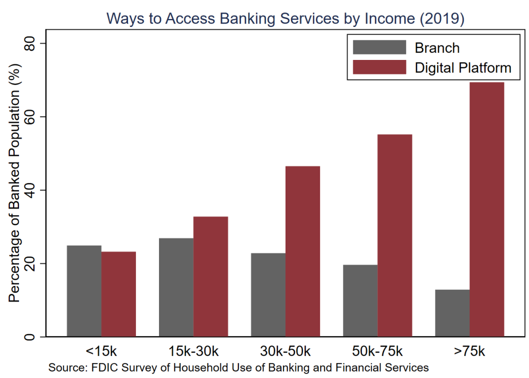
This figure displays the distribution of consumers' preferred way of accessing banking services, as reported in the FDIC Survey of Consumer Use of Banking and Financial Services. The survey asks respondents to indicate their "most common way of accessing their accounts," choosing from options of "Bank teller," "ATM/Kiosk," "Telephone banking," "Online banking," "Mobile banking," and "Other." We classify "Online banking" and "Mobile banking" as digital banking and refer to "Bank teller" as branches. This survey question was added to the survey in 2013. Panel (a) plots the bar chart of shares of banked consumers using branch versus digital banking as the primary ways to access banking services from 2013 to 2019. Panel (b) plots the share of banked consumers by age group using branch versus digital banking as the primary way to access banking services in 2019. Panel (c) plots the share of banked consumers by income group using branch versus digital banking as the primary way to access banking services in 2019.




**(a)** Time Series




**(b)** Cross Section by Age




**(c)** Cross Section by Income



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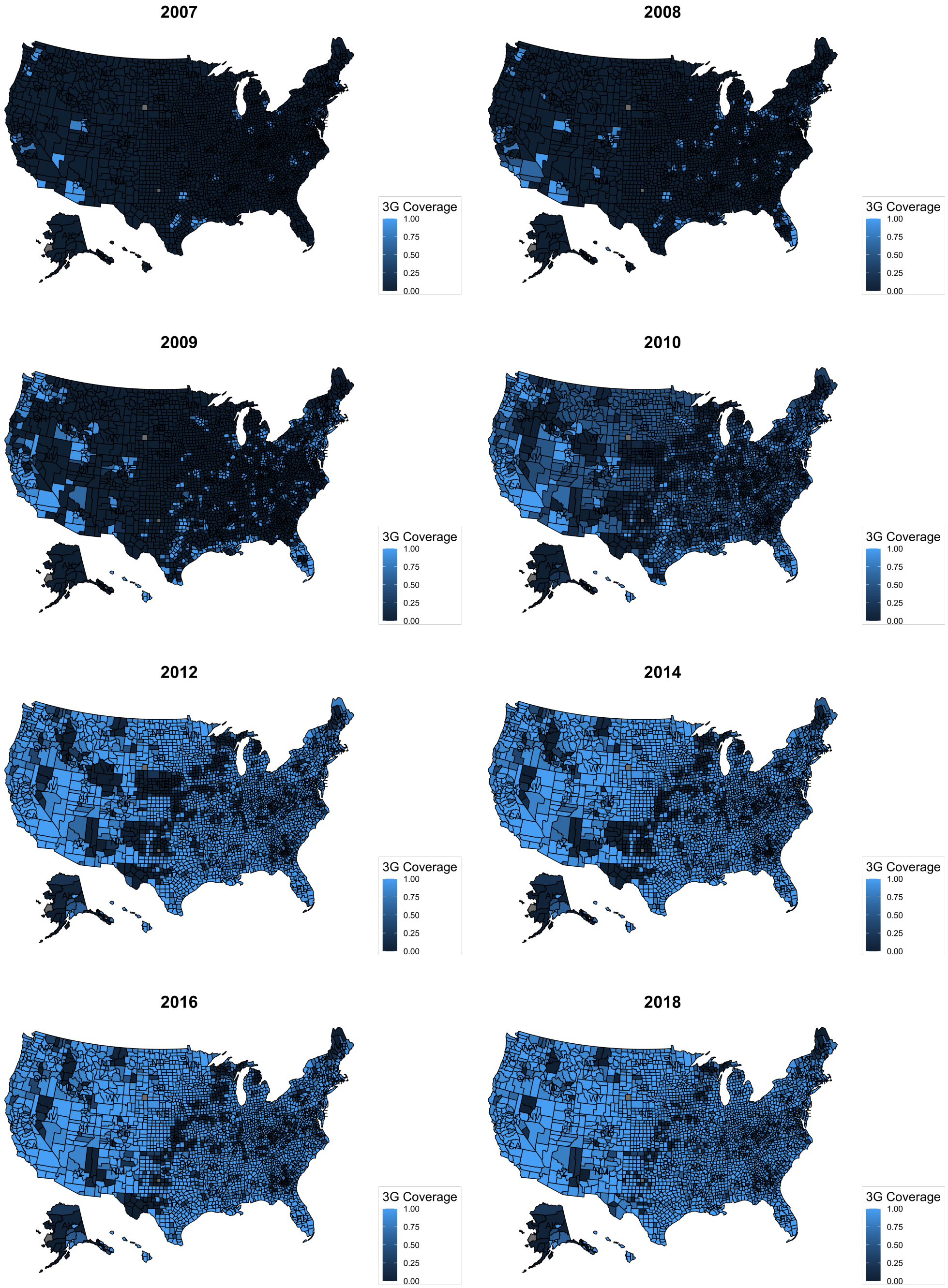
**Figure 2.** Maps of 3G Coverage

This figure displays a map of 3G coverage at the county level in selected years, based on data from Collins Bartholomew's Mobile Coverage Explorer. The 3G coverage is calculated as the weighted average of the value of 3G availability weighted by local population density. To calculate the population density, we used a NASA map that estimates the number of people living within each 1x1-kilometer grid cell across one county's polygon.



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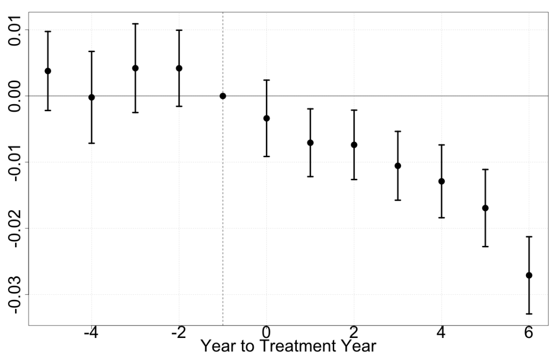
## Figure 3. Difference-in-Difference Event Study

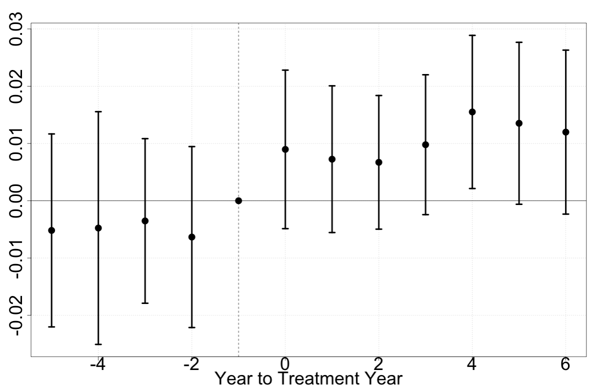
The figure plots Difference-in-Difference (DiD) event study analysis results for county-level local competition with the following specification:

$$Y_{c,t} = \sum_{\tau=-5}^{\tau=6} \beta_\tau \mathbb{I}_{c,\tau} \times \text{Treat}_c + \lambda X_{c,t-1} + \mu_c + \nu_{s,t} + \epsilon_{c,t}.$$

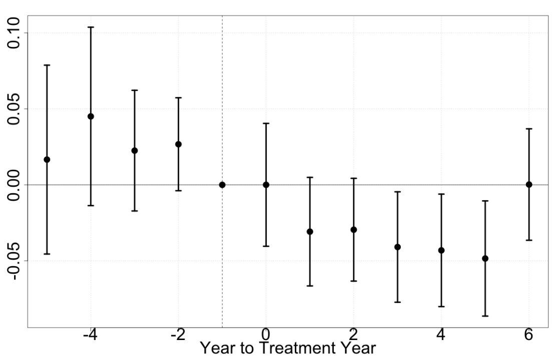
$Treat$ is an indicator variable and set to one if county $c$ experiences an increase in 3G coverage of over 50% within our sample period, and zero otherwise. $\mathbb{I}_{c,\tau}$ is an indicator for whether year $t$ is $\tau$ year since county $c$ experiencing a 50% increase in 3G coverage. The reference year is assigned as $\tau = -1$. To retain all the long-term effects in the data, years with $\tau > 6$ are assigned $\tau = 6$, and years with $\tau < -5$ are assigned $\tau = -5$. The outcome variables are the logarithm of total number of branches (panel a), local branch concentration ($\sum_j (\frac{Branch_j}{\sum_j Branch_j})^2$) (panel b), the mortgage market HHI, constructed using market shares of all loans originated to borrowers in a given county (panel c), and the logarithm of number of lenders originating at least one loan in a given county (panel d). The outcome variables in panels (b) and (c) are standardized to have unit variance. County controls are lagged by one year, including the log of income per capita, the log of county GDP, the log of the total population, the log of the number of banks, the share of the county population that is below age 55, and the share of the population that is White. $\mu_c$ and $\nu_{s,t}$ are county fixed effects and state-year fixed effects. The figures plot estimated $\beta_\tau$, measuring the average difference of $Y_{c,t}$ between year $\tau$ and year $-1$ and its estimated 95% confidence interval. Standard errors are clustered at the state-year level.



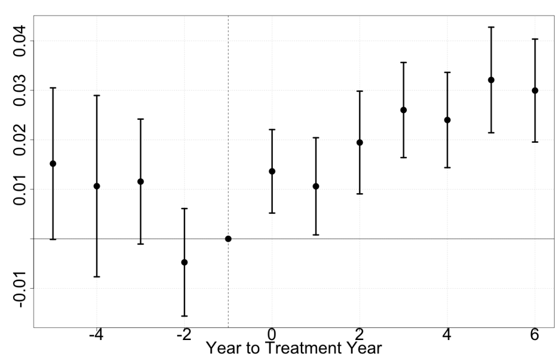

**(a)** Log(1+Branch)




**(b)** Branch Concentration




**(c)** Mortgage HHI




**(d)** Log(1+Lender)



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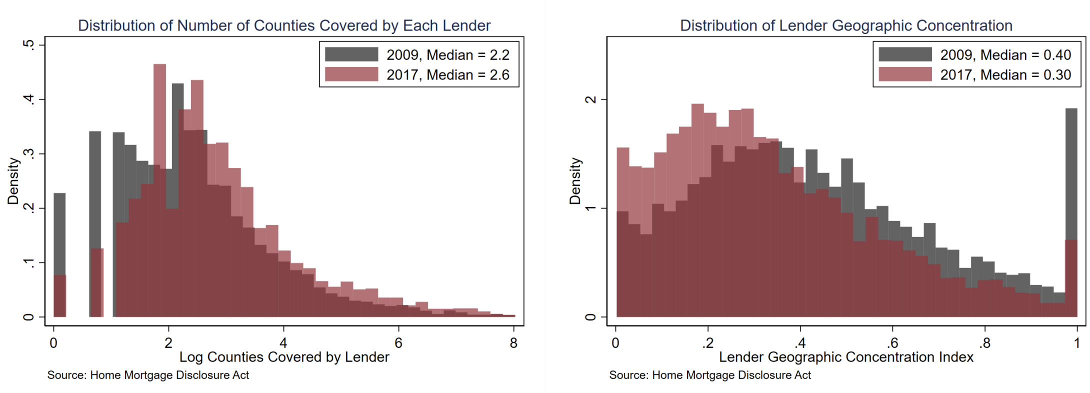
**Figure 4.** Geographic Expansion over Time

This figure plots the distributions of geographic coverage of lenders in 2009 versus 2017, based on data from the Home Mortgage Disclosure Act (HMDA). Panel (a) plots the histogram of the logarithm of the number of counties covered by each mortgage originator in 2009 and in 2017. Panel (b) plots the histogram of the geographic concentration of lenders. The geographic concentration of a lender $j$ is measured as the sum of the squared share of its mortgage origination activity in each county: $\sum_{\mathbb{K}j}(\frac{Volume_{jk}}{\sum_{\mathbb{K}j} Volume_{jk}})^2$, where $\mathbb{K}j$ is the set of counties in which lender $j$ has originated at least one mortgage loan, and $\text{Volume}_{jk}$ is the total loan amount originated by lender $j$ in county $k$.

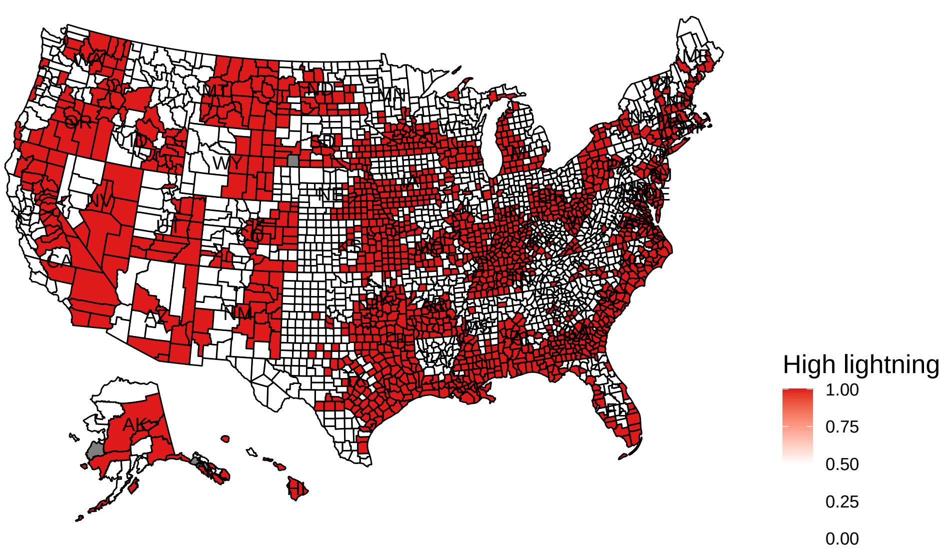



**(a)** Number of Counties

**(b)** Lender Geographic Concentration

**Figure 5.** Map of Counties with High Lightning Strikes Within Each State

This figure plots counties with higher-than-median lightning strike frequency within each state using data from the World Wide Lightning Location Network. The lightning strike frequency is calculated as the amount of the population annually affected by lightning strikes in a county and divided by the total local population. Then we take the average lightning strike frequency in a county across the sample from 2007 to 2018. On the map, we color the counties that have a lightning strike frequency higher than the median for their respective state.



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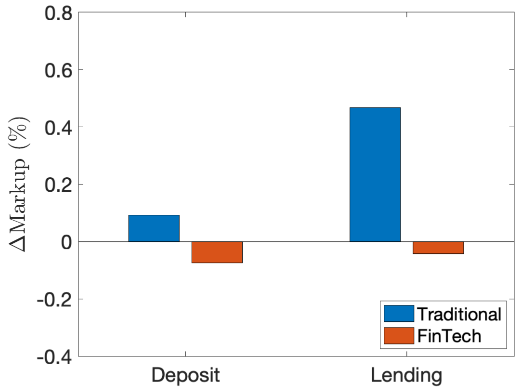
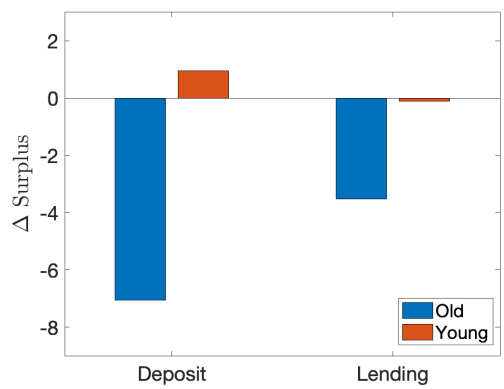
## **Figure 6.** Quantifying the Effects of Digital Disruption

The figure quantifies the impact of digital disruption on banks' markups and consumer surplus. We measure the impact by applying the calibrated changes to digital service quality and marginal costs in Table 7 panel C, while keeping all other parameters the same as their pre-shock values in Table 7 panels A and B. We remove the direct effect of changes in consumer utility function ($\Delta\gamma_i d_F$) from the calculation of changes in consumer surplus. This ensures that our measured change is solely from the banks' endogenous responses to the digital disruption. We assume calibrated $\gamma_y d_F$, $\gamma_o d_F$, $c_F$, and $c_T$ changes in both markets after the digital disruption, mapping to the baseline panel in Table 8. Figure (a) shows how two types of banks adjust their markups before and after the digital disruption, where markups are defined in Equations (11) and (12). Figure (b) presents changes in two types of consumer surplus in both deposit and lending markets, where $\Delta$Consumer Surplus$_i$ is defined in Equation (16).



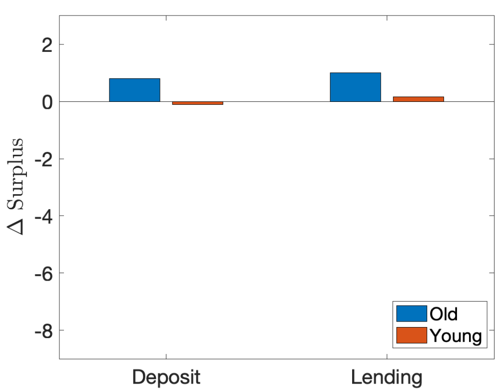

**(a)** Markups



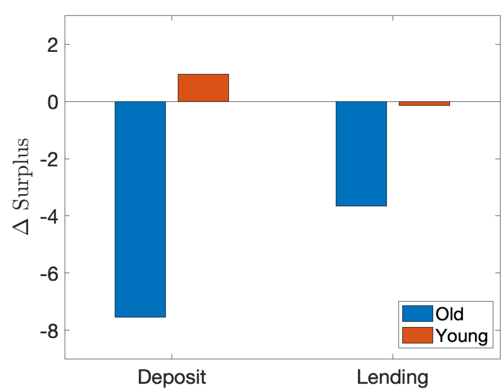

**(b)** Surplus

## **Figure 7.** Spillover Effects across Markets

The figure quantifies the impact of digital disruption on consumer surplus in the deposit market only (figure a) and in the lending market only (figure b), where $\Delta$Consumer Surplus$_i$ is defined in Equation (16). To measure the impact, we apply calibrated changes to digital service quality and marginal costs from Table 7 panel C, while keeping all other parameters the same as their pre-shock values from Table 7 panels A and B. We remove the direct effect of changes in consumer utility function ($\Delta\gamma_i d_F$) from the calculation of changes in consumer surplus. This ensures that our measured change is solely from the banks' endogenous responses to the digital disruption. If digital disruption occurs in the lending (deposit) market only, we assume calibrated $\gamma_y d_F$, $\gamma_o d_F$, $c_F$, and $c_T$ changes only in the lending (deposit) market after the digital disruption, mapping to the the middle two panels in Table 8.




**(a)** Disruption in Deposit Market Only




**(b)** Disruption in Lending Market Only



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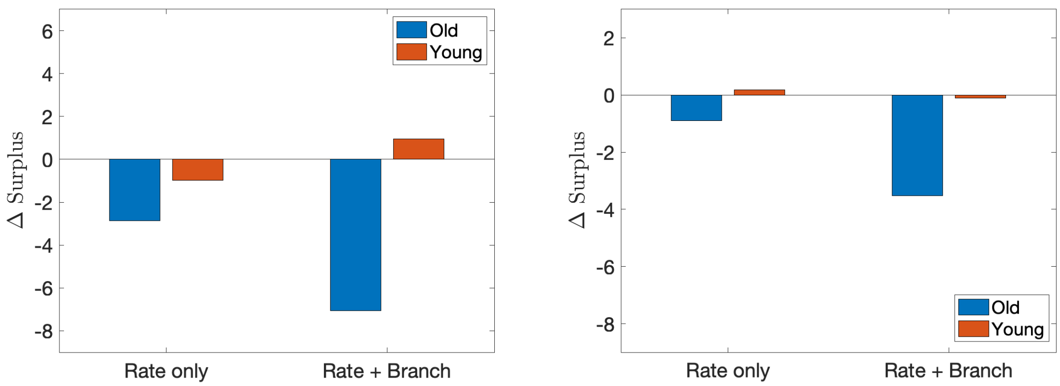
## **Figure 8.** Decomposition: Banks' Endogenous Responses

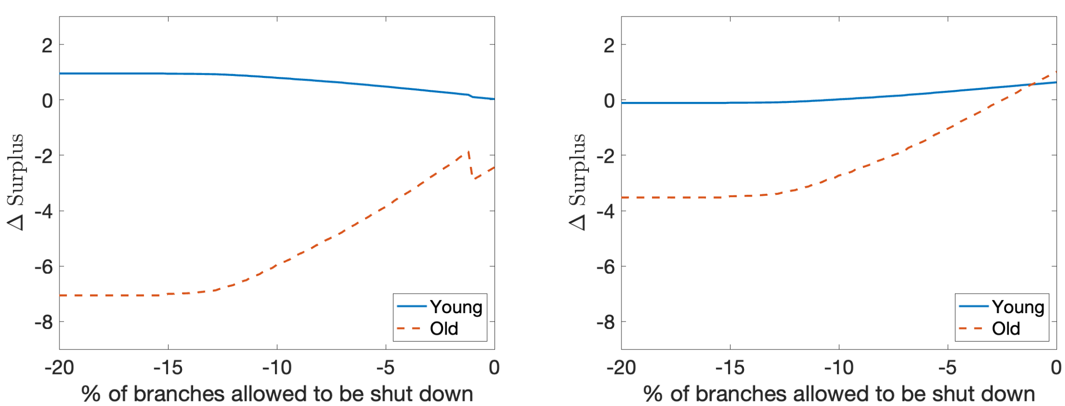
The figures decompose the impact of banks' endogenous responses to digital disruption on consumer surplus, where $\Delta$Consumer Surplus$_i$ is defined in Equation (16). To measure the impact, we apply calibrated changes to digital service quality and marginal costs from Table 7 panel C, while keeping all other parameters the same as their pre-shock values from Table 7 panels A and B. We remove the direct effect of changes in consumer utility function ($\Delta\gamma_i d_F$) from the calculation of changes in consumer surplus. This ensures that our measured change is solely from the banks' endogenous responses to the digital disruption. We assume calibrated $\gamma_y d_F$, $\gamma_o d_F$, $c_F$, and $c_T$ changes in both markets after the digital disruption. We compare two scenarios, 1) banks optimally set their rates only, mapping to the last panel in Table 8; and 2) banks optimally set both rates and branches, mapping to the baseline panel in Table 8. In both scenarios, entry and exit are allowed such that all banks just break even.




**(a)** Depositors **(b)** Borrowers

## **Figure 9.** Counterfactual: Branching Regulation

The figures show the counterfactual results of minimum branching regulation, which restricts the percentage of branches allowed to be shut down after digital disruption. For example, -20% on x-axis means that banks are allowed to shut down at most 20% branches of pre-disruption level. We study how surplus changes for young and old depositors and borrowers before and after digital disruption with minimum branching regulation, where $\Delta$Consumer Surplus$_i$ is defined in Equation (16). To measure the surplus change, we apply calibrated changes to digital service quality and marginal costs from Table 7 panel C, while keeping all other parameters the same as their pre-shock values from Table 7 panels A and B. We remove the direct effect of changes in consumer utility function ($\Delta\gamma_i d_F$) from the calculation of changes in consumer surplus. This ensures that our measured change is solely from the banks' endogenous responses to the digital disruption. We assume calibrated $\gamma_y d_F$, $\gamma_o d_F$, $c_F$, and $c_T$ changes in both markets after the digital disruption.




**(a)** Depositors **(b)** Borrowers



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# Appendix for Online Publication



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# A Data Details

## A.1 Survey Data

The FDIC Survey of Household Use of Banking and Financial Services has been conducted by the FDIC biennially since 2009. Each survey collects responses from around 33,000 consumers, including their bank account ownership, like whether they are banked or unbanked, the primary methods they access their bank accounts if they are banked, why they are unbanked if they don't have a bank account, and saturated set of demographic information. Specifically, respondents' answer the question "unbank" with choices between "Unbanked" and "Has bank account;" the question "Previously banked" with choices between "Once had bank account" and "Never had bank account;" the question "most common way to access account" with the following six choices: "Branch," "ATM/Kiosk," "Telephone banking," "Online banking," "Mobile banking," and "Other;" the question "Unbanked and underbanked" with choices "Unbanked," "Banked: Underbanked," "Banked: Fully banked," "Banked: Underbanked status unknown," where underbanked consumers refer to those who use banks to pay bills and receive income in a typical month, and use nonbank credit in past 12 months.

## A.2 RateWatch Data

**Data construction** For each product of each bank, we take the last surveyed rate within each quarter. Then we aggregate to bank-county-quarter level by taking the average across different branches. We calculate deposit spreads as the difference between Federal Funds Target rates and deposit rates, and calculate loan spreads as the difference between loan rates and Federal Funds Target rates. Federal Fund Target rates are obtained from FRED database.

**Product selection for loans** We first keep the top 30 products with the most observations in the RateWatch loan database and then remove products without applicable rates information, which leave us with 14 products. We group 14 most popular products into mortgage loans, auto loans, and unsecured credit. Mortgage products include "15 Yr Fxd Mtg  175K" and "30 Yr Fxd Mtg  175K"; auto loans include "Auto New - 36 Mo Term," "Auto New - 48 Mo Term," "Auto New - 60 Mo Term," "Auto New - 72 Mo Term," "Auto Used 2 YR - 36 Mo Term," "Auto Used 2 YR - 48 Mo Term," "Auto Used 2 YR - 60 Mo Term," "Auto Used 4 YR - 36 Mo Term," "Auto Used 4 YR - 48 Mo Term," and "Auto



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Used 4 YR - 60 Mo Term"; Unsecured credit loans include "Personal Unsecured Loan - Tier 1" and "Personal Unsecured Loan - Tier 2."

**Discussion on sample issues** We replace bank-state-year fixed effects in Equation (3) with state-quarter fixed effects in Equation (4). This modification eases the constraint of within-bank comparisons and is motivated by two primary reasons. First, existing literature, such as Granja and Paixao (2021), has shown that pricing disparities across regions within a singular bank are minimal. This reduces the statistical power to contrast the pricing strategies of a single bank across various regions. Second, the data collected by RateWatch offers limited insights into cross-county pricing variations. For example, in our sample, only 735 banks provide loan rate data and 1,606 banks offer deposit rate data across multiple counties. In contrast, 5,222 banks have information on branches across more than one county.

In Equation (4), we relax the restriction to use state-quarter fixed effects instead of using bank-state-year fixed effects. This enables us to compare the pricing strategies of more bank-reliant and less branch-reliant banks within an area when it experiences an increase in 3G coverage. However, this specification does not control for time-varying bank-level variations, and hence the effects of omitted bank-specific time-varying shocks cannot be isolated. For instance, the implementation of tighter banking regulations post-Financial Crisis may have a different impact on more branch-reliant versus less branch-reliant banks, affecting their pricing strategies differently. Although our specification has limitations, we find no obvious connection between 3G expansion and banking policies that could explain our results. Therefore, the specification we have used can still provide valuable insights into the impact of 3G expansion on pricing for both types of banks.

## A.3 3G Coverage Data

3G network coverage data is obtained from Collins Bartholomew's Mobile Coverage Explorer. The data spans from 2007 to 2018 at a resolution of 1x1 km binary grid cells, except for the year 2011. The data for 2011 was not collected due to a shift in the company managing the data collection. To account for this missing data, we estimate it by averaging the values in 2010 and 2012. This imputation method has been found to yield reliable results, and the analysis remains robust even when excluding data from 2011.



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# B Alternative IV with Linear Time Trend ($t$)

In Table A6, we conducted 2SLS analyses by incorporating a linear trend that is interacted with the lightning strike indicator, as follows:

$$\text{3G Coverage}_{c,t} = \beta \text{High Lightning}_c \times t + \gamma X_{c,t} + \mu_c + \nu_{s,t} + \epsilon_{c,t}. \tag{17}$$

Compared to Table 2, the coefficients in this analysis are slightly larger in magnitude, but the statistical significance levels are weaker. Although the instrumental variable meets the weak instrument test, as confirmed by the Cragg-Donald test presented in Table A6, the Cragg-Donald F-Statistics in Table 2 are much higher. Therefore, in the main text, we use the instrumental variable with $t^2$, which avoids the potential issue of weak instrument bias and yields more reliable estimates of the causal effect of 3G expansion on banks' decisions.

In the next step, we demonstrate that using a non-linear time trend $t^2$ interacted with $\mathbb{1}[\text{High Lightning}_c]$ in 2SLS gives an unbiased estimation as using a linear time trend $t$ once High Lightning$_c$ satisfies the relevant condition and exclusion restriction of the instrument variable. Here we lay out a simple proof. Suppose the data are generated by a process of the form $y_i = X_i\beta + \epsilon_i$, and $X_i = Z_i t^2 + \nu_i$, where $Z_i$ is the instrument variable with the property that $Z^T\epsilon = 0$, and $t^2$ is the non-linear time trend in our specification. Then $\hat{\beta}_{IV} = (Z^T t^2 X)^{-1} Z^T t^2 y = (Z^T t^2 X)^{-1} Z^T t^2 X\beta + (Z^T t^2 X)^{-1} Z^T t^2 \epsilon \to \beta$.

# C Distributional Effects: Cost of Credit

Our analysis focuses on the impact of 3G expansion on the costs of obtaining bank mortgage loans for younger and older consumers. Younger consumers, who tend to be more tech-savvy, can benefit from intensified competition brought by less branch-reliant banks. In contrast, older consumers, who are more likely to be non-tech savvy and rely on traditional branches, may suffer from worse pricing charged by more branch-reliant banks. To explore this issue, we exploit within-county variations and compare the average loan interest rates paid by different age groups following the expansion of the 3G networks. Leveraging the detailed age information available in the HMDA database since 2018, we estimate a specification that enables us to compare the interest rate gap across different age groups in high 3G coverage regions versus the gap in low 3G coverage regions. We acknowledge that our sample period overlaps with borrower age data for only one year, and we do not have data on depositor characteristics. Hence, we focus on borrowers and loan pricing in this section. Formally, we



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estimate the following specification:

$$
\begin{aligned}
Rate_{b,j,c} =& \beta_1 \text{3G Coverage}_c + \beta_2 \text{3G Coverage}_c \times \text{Borrower Age}_j + \beta_3 \text{Borrower Age}_j \\
&+ \gamma X_j + \mu_c + \epsilon_{b,j,c},
\end{aligned}
\tag{18}
$$

where $b$, $j$, and $c$ index bank, borrower, county, and state, respectively. Since the test sample focuses on 2018 only, we drop the time subscript $t$ in this loan-level specification. $Rate_{b,j,c}$ is mortgage rate of conventional fixed-rate loans charged by bank $b$ in county $c$ on borrower $j$. $BorrowerAge_j$ are a set of indicator variables for borrowers' age range. $\mu_c$ is county fixed effects. To control for loan, borrower, and county characteristics, we include a set of borrower-loan controls $X_j$ in our estimation. These controls include 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, gender, age, and race. The independent variable of interest is the interaction term between 3G coverage and indicator variables for borrowers' age range. By including these controls and fixed effects, we are able to identify the differential effect of 3G penetration on older versus younger borrowers while accounting for other relevant factors.

Table A9 presents the results of our analysis. The negative coefficients on 3G coverage indicate that borrowers below the age of 35 obtain a lower mortgage rate in counties with higher 3G penetration. However, the positive coefficients on the interaction terms in column (1) suggest that borrowers above the age of 34 and below 55 (above 55) pay 8.7 (4.6) percentage-point higher mortgage rates than borrowers below 35 in counties with full 3G coverage compared to the same difference in counties with zero coverage. Importantly, our analysis reveals that the average mortgage rate paid by borrowers between 35 and 55 increases by 3 percentage points (8.7-5.7) after a full 3G penetration. This result supports our hypothesis that non-tech savvy consumers are more likely to rely on branches and are therefore charged higher prices by more branch-reliant banks following 3G expansion. Our findings remain robust to the inclusion of county fixed effects in column (2), which helps to absorb the baseline effect of 3G coverage. In columns (3) and (4), we further verify the results using IV regressions, which yield similar findings



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# D Model Equilibrium

Due to the nested structure of our model, the likelihood $s_i$ can be decomposed into two parts: 1) the likelihood that one type is chosen and 2) conditional on that, the likelihood that bank $j$ is selected. The conditional probability 2) can be calculated using a formula based on the properties of the generalized extreme value distribution:

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

where

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

The term $A_{i,j}$ captures the consumer type $i$'s exponential utility from accessing bank $j$'s services, and the term $Z_{i,t}$ is the sum of her exponential utility assuming she has access to all $t$-type banks. Since we assume that all banks within each type are the same, the conditional probability of choosing a bank from $t$-type equals $\frac{1}{J_t}$. The marginal probability that a $t$-type bank is chosen is given by the following formula:

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

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 proportion of depositors $i$ that stays unbanked is

$$s_{i,0} = \frac{1}{1 + \sum_{t \in \{T,F\}} Z_{i,t}^{\lambda_t}}. \tag{20}$$

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



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tions:

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

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

The difference of $r_j^m - c_j^m$ captures the markup of bank $j$ in the market $m$.

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

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

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:

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

□



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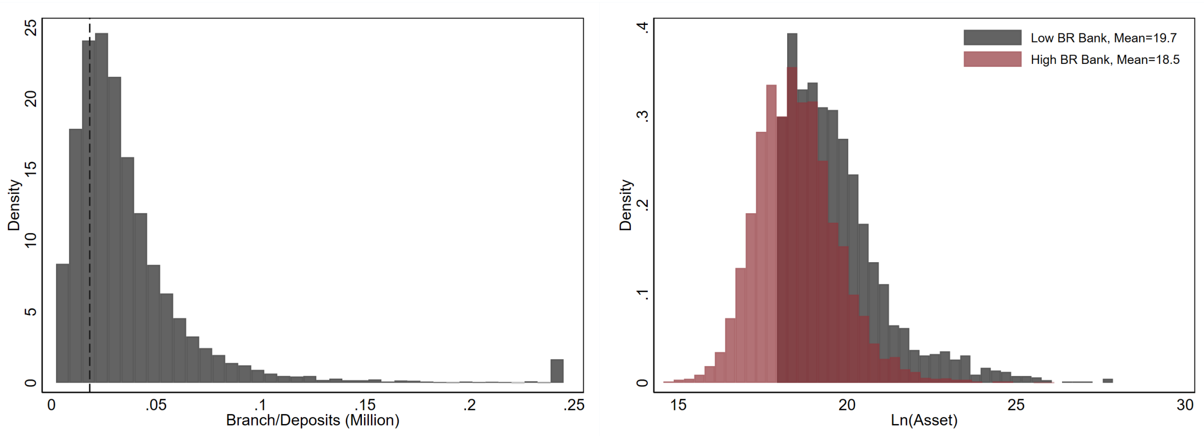
# E Figures and Tables

**Figure A1.** Branch-Reliant Index

The figure plots the distribution of branch-reliant index without standardization (Panel a) and the size distributions of high BR banks and low BR banks (Panel b). Branch-reliant index is calculated as the ratio of a bank's number of branches divided by its total deposits in million, using data in 2007. A low branch-reliant index value indicates that a bank is able to serve a large number of deposits without significant reliance on branches.




**(a)** Branch-Reliant Index

**(b)** Size Distribution

**Figure A2.** Proportion of Unbanked and Underbanked Population

The figure shows the proportion of unbanked and underbanked consumers from 2009 to 2019 using data from the FDIC Survey of Household Use of Banking and Financial Services. The survey was conducted biennially, and the question regarding underbanking was removed from the survey in 2019. Unbanked consumers are those who do not have a bank account, while underbanked consumers are those who use banks to pay bills and receive income in a typical month and have used nonbank credit in the past 12 months.

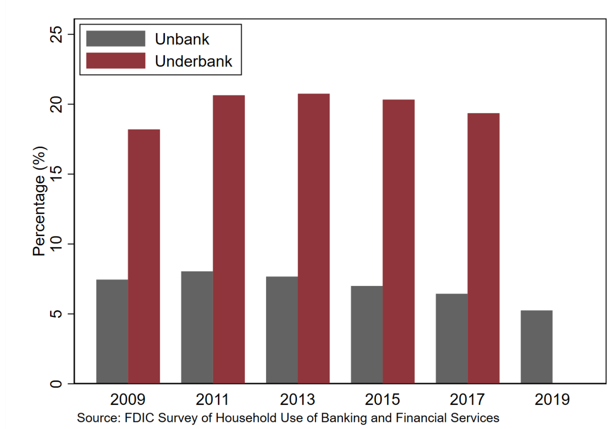





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**Table A1** Premise—Effect of 3G on Access to Banking Services

The table presents results of the impact of 3G coverage on consumers' primary access to banking services, using FDIC Survey of Consumers Use of Banking and Financial Services from 2013 to 2019. The underlying sample contains observations at individual level above 25 years old. Each dependent variables is an indicator variable equals to one if Branch/Mobile Banking/Online Banking/ATM/Telephone Banking is the primary way respondents use to access banking services. 3G coverage is calculated as the proportion of population with access to 3G networks in a MSA region in a year. This survey question was added to the survey in 2013. The observations are weighted to account for non-response and under-coverage. Standard errors are clustered at state-year level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

| | (1)<br>Branch | (2)<br>Mobile Banking | (3)<br>Online Banking | (4)<br>ATM | (5)<br>Telephone Banking |
|---|---|---|---|---|---|
| 3G Coverage | -0.485*** | 0.179*** | 0.108 | 0.200** | 0.009 |
| | (0.127) | (0.061) | (0.153) | (0.102) | (0.021) |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Adjusted $R^2$ | 0.010 | 0.090 | 0.017 | 0.003 | 0.001 |
| Observations | 90,047 | 90,047 | 90,047 | 90,047 | 90,047 |



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## **Table A2** Digital Divide: Cross Section

The table examines the characteristics of consumers who primarily use mobile banking to access banking services, based on data from the FDIC Survey of Consumers Use of Banking and Financial Services from 2013 to 2019. The underlying sample contains observations at individual level above 25 years old. The dependent variable is an indicator variable that equals one if mobile banking is the primary way respondents use to access banking services. This survey question was added to the survey in 2013. The indicator variable Age 35-45 equals 1 if the respondent's age is between 35-45 years old and zero otherwise. The definition for other age groups is the same. Poor equals 1 if the respondent's family income is less than or equal to $30k and zero otherwise. The indicator variable Non-White equals 1 if the respondent is not white and zero otherwise. Low Education equals 1 if the respondent does not have any college degree and zero otherwise. The observations are weighted to account for non-response and under-coverage. Standard errors are clustered at state-year level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

| | Mobile Banking | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Benchmark: Age 25-35 | | | | | |
| Age 35-45 | -0.094*** | | | | -0.089*** |
| | (0.006) | | | | (0.006) |
| Age 45-55 | -0.186*** | | | | -0.180*** |
| | (0.008) | | | | (0.007) |
| Age 55-65 | -0.256*** | | | | -0.244*** |
| | (0.012) | | | | (0.010) |
| Age 65+ | -0.315*** | | | | -0.296*** |
| | (0.017) | | | | (0.012) |
| Benchmark: Above $30k family income | | | | | |
| Poor | | -0.063*** | | | -0.019*** |
| | | (0.006) | | | (0.003) |
| Benchmark: White | | | | | |
| Non-White | | | 0.039*** | | -0.002 |
| | | | (0.004) | | (0.004) |
| Benchmark: Some college education | | | | | |
| Low Education | | | | -0.064*** | -0.022*** |
| | | | | (0.005) | (0.003) |
| MSA×Year FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Adjusted $R^2$ | 0.203 | 0.118 | 0.116 | 0.120 | 0.197 |
| Observations | 90,047 | 90,047 | 90,047 | 90,047 | 90,047 |



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**Table A3** Digital Divide: The Impact of 3G Expansion

The table shows the impact of 3G coverage on consumers' use of mobile banking as their primary means of accessing banking services, using the FDIC Survey of Consumers Use of Banking and Financial Services from 2013 to 2019. The underlying sample contains observations at individual level above 25 years old. The dependent variable "Mobile Banking" is an indicator variable that equals one if mobile banking is the primary way respondents use. This survey question was added to the survey in 2013. 3G coverage is calculated as the proportion of the population with access to 3G networks in an MSA region in a given year. The indicator variable "Age 55+" equals one if the respondent's age is above 55 years old and zero otherwise. "Poor" equals one if the respondent's family income is less than or equal to $30k and zero otherwise. The indicator variable "Non-White" equals one if the respondent is not white and zero otherwise. "Low Education" equals one if the respondent does not have any college degree and zero otherwise. Columns 1 and 2 present OLS results, and columns 3 and 4 present 2SLS results. Controls include indicator variables for consumers who are below 45 years old, college-educated, white, and have a family income above $30k. The observations are weighted to account for non-response and under-coverage. Standard errors are clustered at state-year level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

| | Mobile Banking | | | |
|---|---|---|---|---|
| | OLS | | 2SLS | |
| | (1) | (2) | (3) | (4) |
| 3G Coverage | 0.029 | 0.095 | 12.352*** | 10.883*** |
| | (0.195) | (0.214) | (4.735) | (3.676) |
| Benchmark: Age≤45 | | | | |
| 3G Coverage×Age 55+ | -0.889*** | -0.841*** | -16.321*** | -15.276*** |
| | (0.247) | (0.234) | (2.824) | (2.650) |
| Benchmark: Some college education | | | | |
| 3G Coverage×Low Education | | -0.190** | | -3.598*** |
| | | (0.073) | | (1.087) |
| Benchmark: Above $30k Family income | | | | |
| 3G Coverage×Poor | | -0.138 | | -2.146** |
| | | (0.106) | | (1.053) |
| Benchmark: White | | | | |
| 3G Coverage×Non-White | | 0.117 | | 2.891** |
| | | (0.126) | | (1.303) |
| Controls | ✓ | ✓ | ✓ | ✓ |
| MSA FE | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| Adjusted $R^2$ | 0.170 | 0.170 | - | - |
| Observations | 90,047 | 90,047 | 90,047 | 90,047 |
| Cragg-Donald Wald F-stats | - | - | 131.033 | 53.415 |



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## Table A4 Examples of High Branch-Reliant and Low Branch Reliant Banks

This table provides examples of high branch-reliant banks and low branch-reliant banks based on our branch-reliant index. Column 1 reports the 10 least branch-reliant banks, i.e., the 10 banks that have the lowest branch-reliant index values. Column 2 reports the 10 largest non-branch reliant banks, i.e., the 10 largest banks whose branch-reliant index values are in the lowest quartile. Column 3 reports the 10 largest branch-reliant banks, i.e., the 10 largest banks whose branch-reliant index values are in the highest three quartiles.

| Least Branch-Reliant Banks | Largest Low Branch-Reliant Banks | Largest High Branch-Reliant Banks |
|---|---|---|
| ING Bank | Bank of America | U.S. Bank |
| Merrill Lynch Bank USA | JPMorgan Chase Bank | Regions Bank |
| Countrywide Bank, FSB | Wachovia Bank | Fifth Third Bank |
| Chase Manhattan Bank USA | Wells Fargo Bank | Bank of the West |
| USAA Federal Savings Bank | Citibank | M&T Bank |
| Discover Bank | Washington Mutual Bank | TD BankNorth |
| UBS Bank USA | SunTrust Bank | Charter One Bank |
| Morgan Stanley Bank | BB&T | Colonial Bank |
| E*TRADE Bank | National City Bank | Associated Bank |
| TD Bank USA | HSBC Bank USA | RBC Centura Bank |

## Table A5 First stage of IV regression

The table presents the results of the first stage of IV regression using both county-level and bank-county level samples. 3G coverage is calculated as the proportion of the population with access to 3G networks in a county in a given year. High Lightning equals 1 if the average population-weighted frequency of lightning strikes in county $c$ from 2007 to 2018 is higher than the state median, and 0 otherwise. The time trend variable $t$ represents the year difference between a given year and 2007, and $t^2$ is the square of $t$. The first two columns report results using county-level data, while the last two columns report results using bank-county level data. Standard errors are clustered at state-year level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

| | 100 × 3G coverage | | | |
|---|---|---|---|---|
| | County Level | | County-bank Level | |
| | (1) | (2) | (3) | (4) |
| $\mathbb{1}$(High Lightning) $\times t$ | -0.266** | | -0.238*** | |
| | (0.107) | | (0.084) | |
| $\mathbb{1}$(High Lightning) $\times t^2$ | | -0.024*** | | -0.019*** |
| | | (0.007) | | (0.006) |
| Controls | ✓ | ✓ | ✓ | ✓ |
| County FE | ✓ | ✓ | | |
| State×Year FE | ✓ | ✓ | | |
| Bank-County FE | | | ✓ | ✓ |
| Bank-State-Year FE | | | ✓ | ✓ |
| Adjusted $R^2$ | 0.841 | 0.841 | 0.840 | 0.840 |
| Observations | 36,744 | 36,744 | 459,000 | 459,000 |



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**Table A6** County Level Evidence on Local Competition (Linear Instrument)

This table presents county-level evidence of how 3G affects local competition and banks' branching network using 2SLS. Instead of using Equation (**??**), we adopt a linear trend interacted with lightning strike indicator:

$$\text{3G Coverage}_{c,t} = \beta \text{High Lightning}_c \times t + \gamma X_{c,t} + \mu_c + \nu_{s,t} + \epsilon_{c,t}.$$

Panel A uses the Summary of Deposit (SOD) data. The outcome variable is the logarithm of total number of branches in columns 1-3 and branch concentration in columns 4-6. Branch concentration is calculated as $\sum_j (\frac{Branch_j}{\sum_j Branch_j})^2$, standardized to have a unit variance. Columns 1 and 4 use the full sample. Columns 2 and 5 (3 and 6) use the subsample of young (old) counties. Young (old) counties are defined as counties with the share of below-age 55 population above (below) the median value among all counties. Panel B uses the Home Mortgage Disclosure Act (HMDA) data and restricts to all loans originated by FDIC-insured financial institutions. The outcome variable in column 1 is county-level mortgage market HHI index, constructed using market shares of all loans originated to borrowers in a given county. We standardize the outcome variable to have a unit variance. The outcome variable in column 2 is the logarithm of number of lenders originating at least one loan in a given county in a given year. In both panels, the variable of interest is 3G Coverage, which is calculated as the proportion of population with access to 3G networks in a county in a year. County controls are lagged by one year, including the log of income per capita, the log of county GDP, the log of the total population, the log of the number of banks, the share of the county population that is below age 55, and the share of the population that is White. Standard errors are clustered at state-year level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

Panel A: Branch Network Change (2SLS)

| | Log(1+Branch) | | | Branch Concentration | | |
|---|---|---|---|---|---|---|
| | (1) Full Sample | (2) Young County | (3) Old County | (4) Full Sample | (5) Young County | (6) Old County |
| $\widehat{\text{3G Coverage}}$ | -0.363** | -0.343** | -0.055 | 0.439* | 0.429* | 0.079 |
| | (0.166) | (0.152) | (0.116) | (0.240) | (0.232) | (0.216) |
| County Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| County FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| State-Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 36,744 | 27,414 | 9,085 | 36,646 | 27,360 | 9,040 |
| Cragg-Donald Wald F-stats | 25.087 | 20.933 | 26.922 | 24.127 | 20.230 | 26.375 |

Panel B: Local Competition (2SLS)

| | (1) Mortgage HHI | (2) Log(1+Lenders) |
|---|---|---|
| $\widehat{\text{3G Coverage}}$ | 0.600 | 0.460 |
| | (0.721) | (0.343) |
| County Controls | ✓ | ✓ |
| County FE | ✓ | ✓ |
| State-Year FE | ✓ | ✓ |
| Observations | 33,584 | 33,584 |
| Cragg-Donald Wald F-stats | 14.142 | 14.142 |



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**Table A7** Impact of Lightning Strikes on Local Economic Conditions—Balance Tests

Panel A shows that 3G expansion is associated with local economic conditions, while Panels B and C present the impact of lightning strikes on local economic conditions. In all panels, the dependent variables are county-level economic conditions, including the logarithm of county GDP (Column 1), the logarithm of the total population (Column 2), the unemployment rate (Column 3), the share of the county population below age 40 (Column 4), and the logarithm of the number of banks (Column 5). In Panel A, the independent variable is 3G coverage, which is calculated as the proportion of the population with access to 3G networks in a county in a year. Its coefficient represents the contemporaneous relationship between 3G coverage and local economic conditions. In Panel B, the variable of interest is $\mathbb{1}$(High Lightning), where high lightning strikes represent counties whose average population-weighted frequency of lightning strikes across 2007 to 2018 is higher than the state median. Its coefficient loading represents the difference in local economic conditions in high versus low lightning strike regions. In Panel C, we include the interaction term of $\mathbb{1}$(High Lightning) $\times\, t^2/10000$, where $t$ is the year difference between a given year and 2007. The interaction term captures the growth difference in local economic conditions in high versus low lightning strike regions. Non-interaction terms are not reported. Standard errors are clustered at the state level. Numbers in parentheses are standard errors. $^{*}$, $^{**}$, $^{***}$ represent statistical significance at 10%, 5% and 1% level, respectively.

Panel A

| | (1) log(CountyGDP) | (2) log(TotalPop) | (3) Unemployment Rate | (4) Share of Pop Under 40 | (5) log(# Bank) |
|---|---|---|---|---|---|
| 3G Coverage | 1.364$^{***}$ | 1.136$^{***}$ | −1.666$^{***}$ | 0.001 | 0.495$^{***}$ |
| | (0.100) | (0.114) | (0.303) | (0.003) | (0.051) |
| Observations | 36,756 | 37,296 | 37,308 | 37,296 | 37,308 |
| Adjusted $R^2$ | 0.141 | 0.115 | 0.055 | 0.0001 | 0.095 |

Panel B

| | (1) log(CountyGDP) | (2) log(TotalPop) | (3) Unemployment Rate | (4) Share of Pop Under 40 | (5) log(# Bank) |
|---|---|---|---|---|---|
| $\mathbb{1}$(High Lightning) | 0.122 | 0.136 | 0.058 | 0.004 | 0.053 |
| | (0.116) | (0.128) | (0.141) | (0.003) | (0.062) |
| Observations | 42,877 | 43,507 | 43,521 | 43,507 | 43,521 |
| Adjusted $R^2$ | 0.001 | 0.002 | 0.0001 | 0.001 | 0.001 |

Panel C

| | (1) log(CountyGDP) | (2) log(TotalPop) | (3) Unemployment Rate | (4) Share of Pop Under 40 | (5) log(# Bank) |
|---|---|---|---|---|---|
| $\mathbb{1}$(High Lightning) $\times\, t^2/10000$ | −0.871 | 0.387 | 7.831 | −0.032 | 0.169 |
| | (1.252) | (0.522) | (8.177) | (0.091) | (0.480) |
| Observations | 42,877 | 43,507 | 43,521 | 43,507 | 43,521 |
| Adjusted $R^2$ | 0.006 | 0.002 | 0.097 | 0.107 | 0.002 |

# **Table A8** Placebo Tests

This table presents the impact of lightning strikes on county-level branch network changes and local competition *before* the rollout of 3G networks, covering the period from 2002 to 2006. The dependent variables are the logarithm of the total number of branches in column 1 and branch concentration in column 2, both constructed using the Summary of Deposit (SOD) data. Branch concentration is calculated as $\sum_j (\frac{Branch_j}{\sum_j Branch_j})^2$, standardized to have a unit variance. The last two columns uses the Home Mortgage Disclosure Act (HMDA) data and restricts to all loans originated by FDIC-insured financial institutions. The outcome variable in column 3 is county-level mortgage market HHI index, constructed using market shares of all loans originated to borrowers in a given county. We standardize the outcome variable to have a unit variance. The outcome variable in column 4 is the logarithm of number of lenders originating at least one loan in a given county in a given year. High lightning strikes represent counties whose average population-weighted frequency of lightning strikes across 2002 to 2006 is higher than the state median. The variable of interest is the interaction term $\mathbb{1}$(High Lightning) $\times t^2/10000$, which serves as the instrument variable used in the first stage of our IV regression (15). County controls are lagged by one year, including the log of income per capita, the log of county GDP, the log of the total population, the log of the number of banks, the share of the county population that is below age 55, and the share of the population that is White. Standard errors are clustered at state-year level. Numbers in parentheses are standard errors. $^*$, $^{**}$, $^{***}$ represent statistical significance at 10%, 5% and 1% level, respectively.

| | Branch Network Change | | Local Competition | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Log(1+Branch) | Branch Concentration | Mortgage HHI | Log(1+Lenders) |
| $\mathbb{1}$(High Lightning) $\times t^2/10000$ | -0.181 | 0.345 | -7.166 | 2.375 |
| | (1.032) | (0.295) | (9.462) | (2.325) |
| County Controls | ✓ | ✓ | ✓ | ✓ |
| County FE | ✓ | ✓ | ✓ | ✓ |
| State-Year FE | ✓ | ✓ | ✓ | ✓ |
| Observations | 15,175 | 15,175 | 15,053 | 15,053 |
| Adjusted $R^2$ | 0.998 | 0.983 | 0.783 | 0.989 |



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**Table A9** Distributional Effect of 3G — Cost of Credit

This table presents the distributional effect of 3G expansion in terms of cost of credit. The underlying sample includes conventional fixed rate loans originated in 2018 from the Home Mortgage Disclosure Act (HMDA) data. The dependent variable is mortgage interest rate. Columns 1-2 are baseline OLS. Columns 3-4 are 2SLS. The predicted 3G Coverage in 2018 in 2SLS is taken from the first stage regression of column (2) in Table A5. Controls include log of loan size, loan-to-value ratios, debt-to-income ratios, log of income, race, loan terms, age, and their interaction terms with 3G coverage. Standard errors are clustered at the county level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

| | OLS | | 2SLS | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| 3G Coverage | -5.690*** | | -4.847*** | |
| | (1.8947) | | (1.766) | |
| Benchmark: Age≤35 | | | | |
| 3G Coverage×Age∈ [35, 55) | 8.744*** | 7.835*** | 6.286*** | 6.874*** |
| | (1.441) | (1.413) | (1.102) | (1.108) |
| 3G Coverage×Age 55+ | 4.552*** | 3.537** | 3.745** | 4.285** |
| | (1.948) | (1.867) | (1.969) | (2.006) |
| Controls | ✓ | ✓ | ✓ | ✓ |
| State FE | ✓ | | ✓ | |
| County FE | | ✓ | | ✓ |
| Adjusted R2 | 0.193 | 0.203 | 0.193 | 0.203 |
| Observations | 3M | 3M | 3M | 3M |



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