The Digital Banking Revolution: Effects on Competition and Stability

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ABSTRACT

How does the digital revolution affect bank competition and financial stability? I use hand-collected data and a novel identification strategy to show that after adopting digital platforms, banks *branchlessly* operate in more markets, and mid-size banks – those with relatively high quality digital platforms but without extensive branch networks – grow faster. Further, bank balance sheet composition tilts to uninsured deposits on the funding side, and to high income borrowers on the loan side. To disentangle the underlying mechanisms and quantify aggregate effects, I build a structural model of the U.S. banking system and compare the observed digital equilibrium to a counterfactual without digital platforms. The model allows for endogenous adoption of digital platforms, branch networks, market entry, and accounts for digitalization among non-banks. Digitalization decreases local and national market concentration, and average markups fall in deposit and loan markets, holding fixed the size of the banking sector. Consumers capture most of the surplus created by digitalization, however it accrues mostly to wealthier segments of the economy. As for stability, it increases the average market share of lightly-regulated mid-sized banks by 29%, increases the uninsured deposits ratio of the banking sector by 9% while re-sorting uninsured deposits towards larger digital banks, and doubles credit risks associated with lending in market segments that are less-well served by digital technologies. In sum, digital banking increases competition and poses risks to financial stability.

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I. Introduction

Over the past decade, the digital revolution has had a profound effect on banking. Digital banking platforms – mobile applications and websites – have become widespread. This new technology serves as an alternative to brick-and-mortar branch networks: It has become the leading way consumers access and banks supply financial services (FDIC, 2021). As a result, the digital revolution may affect how banks compete. Competition in banking is of particular interest due to its implications for financial stability, which affects the economy at large.

A priori, the way that digital banking platforms affect competition is unclear. Digital banking may alter both the size distribution of banks as well as the composition of services they provide. For instance, in what concerns size, scale economies in digital service provision may allow the largest banks to capture additional market share, but it also may allow smaller banks to compete more effectively with the extensive branch networks of these large banks.[1] Further, the effects on competition may vary across banking products: If a certain type of depositor or loan customer has a high preference for obtaining digital services, or becomes cheaper for digital banks to provide services for, then this segment of the market will grow and digital banks will gain market share. Which of these forces dominate is ultimately then an empirical question.

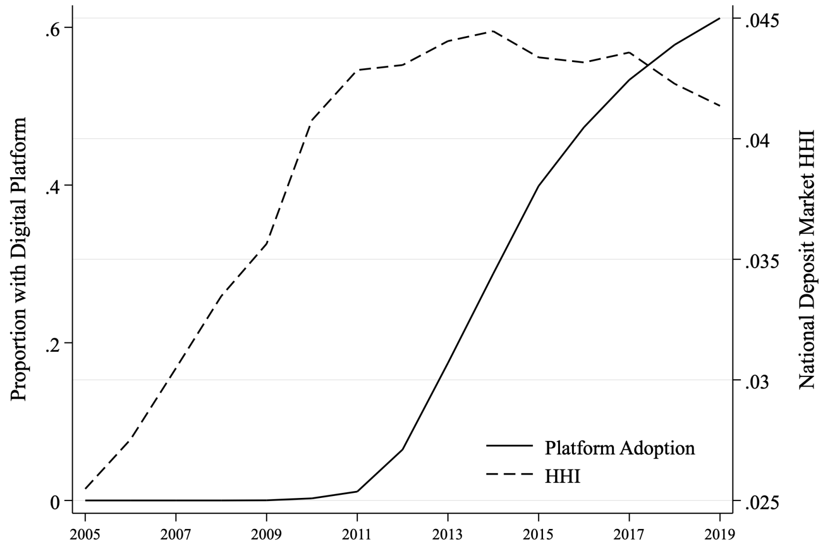
In this paper, I show that digital platforms have increased competition in deposit and loan markets by allowing mid-sized banks — those with relatively high quality digital platforms but without extensive branch networks — to gain market share through higher demand and lower costs. As a result, banks *branchlessly* enter local markets, markets become less concentrated, and customers enjoy a greater share of the surplus created by this technological innovation. Further, I find that the effects are uneven across market segments and thereby lead to changes in banks' balance sheet composition. Digital banks increase their share of uninsured deposits while reducing their share of loan originations to low income borrowers, partially driven by a lower ability to digitally screen or monitor this market segment.

The implications for financial stability are apparent: The increase in size and geographic reach of mid-sized banks makes them more important from a financial stability point of view. Digitalization also alters the probability of bank distress by increasing funding instability as measured by banks' share of uninsured deposits, and by leading to elevated credit risks in market segments that are less-well served by digital technologies. Thus, my analysis informs where risks may build up in the banking sector as a result of the digital revolution, which is of interest to policymakers navigating the new technological landscape.

[1] Indeed, there are mixed views in the press. A McKinsey report (link) argues that digitalization favors consolidation while a KPMG report (link) instead suggests that it will lead to increased competition.

Figure 1. Banking Sector Digital Platform Adoption and Market Concentration

In this figure, the solid line plots the proportion of U.S. commercial banks that have a mobile application in a given year, annually from 2005 to 2019. A bank is designated as having a commercial bank application in a given year if its mobile application was available at the beginning of that year, and has at least 5 reviews. The dashed line plots the national deposit market HHI. Application data is hand-collected and deposit volumes come from the FDIC SDI.



In my analyses I confront two empirical challenges: a lack of data on bank digital platform adoption, and the endogeneity of banks' adoption decisions. I meet the first challenge by hand-constructing a detailed panel data set related to the introduction of digital banking platforms for the universe of U.S. commercial banks. I proxy for digital platforms more broadly using mobile platforms and show that the development of banks' mobile platforms and websites are highly correlated. My main measure of digital banking is an indicator variable at the bank-year level that tracks whether the bank has a mobile application at the start of that year.

Figure 1 shows that the rise of digital platforms coincides with an attenuation in banking sector consolidation, which provides one indication that the competitive landscape of the banking sector has undergone changes. Of course, during this period other forces may also have altered the landscape of the banking sector, including large changes in the regulatory environment. For this reason, I conduct my analysis using only cross-sectional variation. To address the second challenge of endogeneity concerns, I introduce a novel shift-share instrument that leverages plausibly exogenous variation in banks' exposure to mobile technology during the onset of the digital banking era.

I use my instrument to provide reduced form evidence on how digital platform adoption affects bank-level outcomes. First I look at banks' geographic expansion and growth. After adopting digital platforms, banks expand their service provision geographically by originating loans in new areas without opening new branches. Mid-sized banks, i.e. those with assets between \$10 and \$100 Billion, grow larger after adopting digital platforms. I show that digital platform quality is increasing in bank size, while banks' branch quality is decreasing in bank size. Thus, customers who have a mix of transactional and relationship-based banking needs may prefer to bank with mid-sized banks — those with relatively high quality branches and digital platforms — relative to small or large banks that excel solely in branch or digital services. Further, banks' deposit growth increases even after controlling for loan growth, which combined with their geographic expansion provides evidence that digitalization alters bank competition in both deposit and loan markets independently.

Second, I turn to compositional effects across banking products. After adopting digital platforms banks increase their ratio of uninsured deposit funding, and increase their ratio of loans originated to high income borrowers. I provide evidence that the deposit market results are driven by an inflow of corporate deposits to digital banks, either due to corporations preferring digital banking, or banks finding it cheaper to serve corporate customers digitally. For loan markets, I use detailed applications and rejections data to provide evidence that the results are likely due to a combination of demand and supply effects.

The reduced form analyses confirms the effect of digitalization on several outcomes of interest. In order to identify the specific economic mechanisms driving these outcomes, I next turn to a structural model. This approach also allows quantification of the aggregate effects on competition and financial stability. Finally, the model evaluates the effects of digitalization on welfare: consumer surplus and bank profits.

I estimate a structural model of the U.S. banking sector using techniques from the empirical IO literature. My model has three key ingredients. First, digital platforms and branches are substitutes in bank supply and customer demand, and the degree to which they are interchangeable is allowed to vary both across market segments and banks' business models. Second, banks' digital platforms, branches, and geographic scope are endogenously determined. Specifically, banks decide whether or not to adopt digital platforms, determine their branch networks, and make county entry decisions before monopolistically competing in deposit and loan markets. Third, in the model I allow for a non-bank outside option and capture digitalization among these non-banks, such as the rise of Quicken Loans, through specifying the digital services provided by this outside option.

My model builds on a growing literature that models discrete choice demand systems for banking services (see Dick (2008), Egan et al. (2017), Buchak et al. (2018b), Wang et al. (2020), Xiao (2020), Diamond et al. (2020) based on the methods introduced by Berry et al. (1995)). I augment this framework by allowing for the endogeneity of digital platforms and use my shift-share instrument for identification, providing the first estimate of customers' demand elasticity for digital banking services. This estimate is useful not only to understand the effects of digital platform adoption by traditional banks, but also digitalization in other areas of the banking sector such as the introduction of CBDC, as used in Whited et al. (2022a). I model a rich supply side to capture how digital platforms and branches affect banks' variable cost structure, and use moment inequality techniques to estimate banks' fixed investment costs (Manski, 1975, 1987, Ishii, 2004, Pakes et al., 2015, Pakes and Porter, 2016, Wollmann, 2018). Additionally, I develop a technique to estimate how banks' monitoring or screening activity depends on branches and digital platform technology and thereby affects banks' expected loan losses, which contribute to banks' costs of providing loan services.

Estimation of the model parameters allows for identification of the mechanisms driving the aforementioned reduced form effects. First, banks expand geographically because high income borrowers have high demand for banks with digital platforms, even in the absence of a local branch. Second, the disproportionate growth of mid-sized banks is driven by these banks having the largest demand response among insured depositors to digital platforms, along with a significant reduction in their marginal costs. This is consistent with these banks operating both digital platforms and branches of relatively high quality. Third, the disproportionate growth of uninsured deposits is due to these depositors having a high demand for digital platforms. Fourth, the low growth of loans to low income borrowers is driven by both a lack of demand response by these borrowers to digital platforms, as well as lower ability of banks to screen these borrowers once they adopt digital platforms.

With the model estimates in hand, I turn to the central research question of this paper: what are the aggregate effects of digital platforms on bank competition and financial stability?

I quantify aggregate effects of digitalization on competition in the U.S. banking sector by comparing the observed equilibrium with a counterfactual equilibrium in which digital platform technologies are not available. The evidence on concentration, market integration, markups, and surplus speak to increase in competition in banking. First, this technology reduces banking market concentration: the HHI of the national deposit market, a common measure of industry consolidation, decreases by 6.9%. Second, in addition to becoming less consolidated, the banking sector becomes *branchlessly* more integrated: there are on average 8.2% more banks providing banking services in a given market after the availability of digital platforms, even as the average bank closes 5.8% of their branches. Third, the value-weighted markup that customers face in deposit and loan markets, holding fixed the share of the outside option, falls. Lower markups are indicative of increased competition as prices approach marginal costs. Fourth, expected consumer surplus increases by 26.6% while aggregate bank profits remain unchanged, suggesting that customers are able to capture more of the total surplus created in the digital economy. A large portion of the gains in consumer surplus accrue to uninsured depositors and high income mortgage borrowers, suggesting that digitalization disproportionately favors wealthier segments of the economy. The unchanged aggregate bank profit masks large heterogeneity across the bank size distribution: the profits of large and mid-sized banks increase while those of small banks with under $10B in assets fall, consistent with digital platforms increasing the economies of scale in banking.

Next, I evaluate the implications of these changes for financial stability. First, as a result of the flattening of the bank size distribution, mid-sized banks in particular grow in size and geographic scope. I find that mid-sized banks with assets between $10B and $100B on average provide 29.0% more services within the banking sector, and serve 6.9% more markets. This is of concern given the weakening regulatory oversight of mid-sized banks in recent years, including the 2018 Economic Growth, Regulatory Relief and Consumer Protection Act which exempted U.S. banks with under $250 billion in assets from the Dodd-Frank Act's banking regulations.[2] This finding also suggests that digitalization may have played a role in the growth of regional banks which ultimately resulted in regulators classifying their failures during early 2023 as a systemic risk to the financial system.

Second, I consider implications for banks' credit risks, as measured by changes to their expected loan losses. First I find that the banking sector's expected losses per dollar of loan origination decreases by 37.9% upon adoption of digital platforms. Next, I look separately at expected loan losses for lending in low and high income market segments. I find that the banking sector's loss per dollar of loan to high income borrowers decreases by 48.4%, but that it *increases* by 119.2% for low income borrowers. This result suggests that the digitalization of banking may lead to a build up of credit risks within segments of the banking system that are less well served by digital technologies. This is particularly worrying because banks are uniquely positioned to evaluate risks that are not amenable to the codification that digitalization requires, and thus digital banking may erode banks' "specialness" in this dimension (Stein, 2002).

Third, I consider implications for banks' funding risk. I find that the aggregate uninsured deposits ratio of the banking sector increases by 8.5%, and further that that there is a re-sorting of uninsured deposits towards larger banks with digital platforms within the banking sector. Digital banks with over $100B in assets increase their uninsured deposit ratio by 17.6%, whereas digital banks with between $10B and $100B in assets increase their uninsured deposit ratio by 7.7%. Uninsured depositors have a higher sensitivity to both interest rates as well as bank risk, as can be seen from the results of the deposit demand estimation, and as highlighted by the banking instability in early 2023 (Jiang et al., 2023). As a result, both

[2] Source: (link)

the banking sector as a whole and digital banks in particular have a flightier deposit base in the digital equilibrium, as measured by their uninsured deposit ratio.

A. Related Literature

In this paper I draw from and contribute to four related strands of literature. First, I quantify how digital platforms alter competition in the banking sector by allowing banks to capture market share in areas where they do not operate branches. This relates to large literatures studying bank competition and market integration, which have traditionally highlighted the importance of branch networks (Strahan et al., 2003, Acharya et al., 2011, Gilje et al., 2016, Drechsler et al., 2017, Honka et al., 2017, Hatfield and Wallen, 2022).[3] Bank market power affects monetary policy transmission (Scharfstein and Sunderam, 2016, Drechsler et al., 2017, Xiao, 2020, Diamond et al., 2020), bank risk taking (Boyd and De Nicolo, 2005, Martinez-Miera and Repullo, 2010), and credit provision (Petersen and Rajan, 1995, Boot and Thakor, 2000, Buchak and Jørring, 2021), while the integration of banking markets matters for local economic growth and volatility (Bernanke, 1983, Jayaratne and Strahan, 1996, Calomiris, 2000, Morgan et al., 2004, Acharya et al., 2011, Iyer et al., 2014, Camanho and Carvalho, 2021, Kundu et al., 2021, Kundu and Vats, 2021, Gelman et al., 2023) and the geographic scope of bank health shocks that are transmitted to the real economy (Khwaja and Mian, 2008, Bord et al., 2015, Loutskina and Strahan, 2015, Paravisini et al., 2015, Berrospide et al., 2016, Cortés and Strahan, 2017, Levine et al., 2020, Iyer et al., 2023). My empirical and quantitative analysis complements Vives and Ye (2022) who analyze how IT adoption affects bank competition within a theoretical framework. Specifically, I find that digitalization makes mid-sized banks — those with relatively high quality digital platforms and branches — more competitive, gaining market share in deposit and loan markets. This relates to Jiang et al. (2020), who find that access to deposit funding drives bank size, particularly for smaller and mid-sized banks, via a structural equilibrium model combined with data on capital structure decisions of banks and shadow banks.

Second, I show that the development of digital platforms alters banks' ability to monitor or screen borrowers in a way that varies across market segments, leading to higher per-unit expected loan losses and lower growth in loans to low income borrowers. This relates to a large and seminal literature in banking emphasizing banks' screening and monitoring abilities (Petersen and Rajan, 1994, Fisman et al., 2017, Drexler and Schoar, 2014), and on how banks' use of soft or intangible information may be altered by information technologies (Petersen and Rajan, 2002, Berger et al., 2005, Liberti and Petersen, 2019, Modi et al., 2022)

[3]Branch networks have also been emphasized in the literature on financial inclusion, see Célerier and Matray (2019), Cramer (2021), Sakong and Zentefis (2023) and references within.

or organizational structure (Stein, 2002, Berger and Udell, 2002, Loutskina and Strahan, 2011, Chen et al., 2017, Skrastins and Vig, 2019). An adjacent strand of literature studies the lending behavior of non-bank fintechs, finding in some instances that these lenders reach customers that are traditionally under-served by the banking sector, including lower income and minority borrowers (Jagtiani and Lemieux, 2019, Donaldson et al., 2021, Howell et al., 2021, Di Maggio and Yao, 2021, Chernenko et al., 2022, 2023, Erel and Liebersohn, 2022, Degerli and Wang, 2022). However, other work highlights that reliance on codifiable information can lead to systemic biases in which customers receive credit from these fintechs or that these fintechs do not appear to be targeting under-served populations (Buchak et al., 2018b, Blattner and Nelson, 2021, Balyuk et al., 2022, Fuster et al., 2019, 2021, 2022). Importantly, I focus on on-balance-sheet lending for which banks take credit risk, whereas non-bank fintech lenders sell the majority of their originated loans, largely to government agencies (Buchak et al., 2018a). My findings suggest an important caveat to the narrative that technology expands credit access to underserved populations, in that it may do so mainly for government subsidized lending rather than for loans that stay on lenders' balance sheets. I connect banks' ability to accurately screen or monitor their borrowers to financial stability, as highlighted during the great financial crisis (Mian and Sufi, 2009, Benmelech and Dlugosz, 2010, Keys et al., 2010, Demyanyk and Van Hemert, 2011, Adelino et al., 2016, Lewellen and Williams, 2021).

Third, I show that the development of digital platforms have implications for banks' deposit composition and therefore bank funding stability. This relates to a seminal literature that highlights banks' key role of maturity transformation and which studies the effects of banks' funding composition (Diamond and Dybvig, 1983, Goldstein and Pauzner, 2005). Notably, Egan et al. (2017) studies the financial stability implications of uninsured depositors' sensitivity to bank distress. In contrast, Calomiris and Jaremski (2019) show that uninsured deposits may discipline banks, curbing risk-taking. Recently the bank runs during the 2023 banking crisis spurred a set of papers studying bank funding stability (Jiang et al., 2023, Drechsler et al., 2023, Haddad et al., 2023). While this paper focuses on how digital banking affects deposit composition across insured and uninsured depositors, in a follow-on work Koont et al. (2023) show that digital banks also face higher deposit outflows for each deposit market segment in response to increases in interest rates, leading to a lower deposit franchise value for a given level and composition of deposits, and Benmelech et al. (2023) provides complementary evidence that banks with lower branch density experienced greater deposit outflows during the 2023 banking crisis.

Fourth, my analysis builds on a body of work that studies the effects of banks' technology adoption (see Vives (2019) for an overview) and the literature on technological innovations more broadly (Kogan et al., 2017, Kelly et al., 2021). I join two recent papers in studying digital banking during the era of mobile applications.[4] Jiang et al. (2022) examines implications of digital banking for financial inclusion and finds that digital customers benefit from the intensified bank competition while non-digital customers face the risk of financial exclusion. My findings are complementary to this work in that I study how market segments are differentially affected by digitalization, and focus on resulting changes in banks' balance sheet composition and implications for financial stability. Haendler (2022) examines the implications of mobile banking for small community banks and finds that they are slower to adopt these technologies, and subsequently lose deposits and reduce small business lending. My findings are consistent with these results, as I quantify the effects of digital banking across the bank size distribution using my structural framework and find that digital banking erodes the profits of small banks, even among those who are able to adopt digital platforms. Moreover, I am the first to endogenize digital platform adoption within a quantitative model of the U.S. banking sector, and I use a novel identification strategy to evaluate the aggregate effects of digital platform adoption on competition and financial stability.[5]

The remainder of the paper is organized as follows. Section II describes the data and institutional details related to digital platforms. Section III explains the identification strategy. Section IV reports the reduced form analyses. Section V introduces the structural empirical model of the U.S. banking sector. Section VI estimates and reports the model parameters. Section VII evaluates counterfactual exercises. Section VIII discusses the broader implications of the findings and concludes.

[4] My paper also relates to the growing literature on the use of technology by financial intermediaries in general, including fintech non-banks. This includes non-bank mortgage (Buchak et al., 2018b) and small business lending (Ghosh et al., 2022, Howell et al., 2022, Erel and Liebersohn, 2022, Balyuk et al., 2022); internet-only banks (DeYoung, 2005, Erel et al., 2023); fintech and cost of financial services (Mishkin and Strahan, 1999, Berger and Mester, 2003, Philippon, 2016, Fang et al., 2023); open banking (Babina et al., 2022); CBDC (Schilling et al., 2020, Whited et al., 2022b).

[5] The forces that drive bank technology adoption in my model framework relate to a literature studying the determinants of banks' technology adoption more broadly. See Karshenas and Stoneman (1993) for a general categorization of the determinants of technology adoption in competitive environments; Haendler (2022) for the determinants of mobile banking adoption; Hernández-Murillo et al. (2010) and Sullivan and Wang (2013) for early internet banking adoption; Akhavein et al. (2005) and Mishra et al. (2019) for credit scoring; He et al. (2021) and Modi et al. (2022) for general information technology investments.

II. Data and Institutional Details

A. Data

A.1. Digital Banking Platforms

There is not an extant data set that documents digital platform adoption by U.S. banks. A first contribution of this paper is the construction of such a data set for the universe of U.S. commercial banks. I hand-collect the release date of each bank's earliest mobile application on either the Apple or Android App Store. I additionally collect data on each banking application's features and its rating. In order to do this, I query the Apple iTunes Search API[6] for each bank and manually confirm that each match is accurate. However, often banks delete old applications when releasing a new version rather than updating their existing application, so that looking only at the current versions of mobile applications results in release dates that are later than a bank's original date of technology adoption. In order to correct for this, I manually search each mobile application in `Data.ai`'s database and trace back the history for each bank to find the original release date of their first application across either the Apple or Android app store. To avoid including applications that may not be functional, I exclude a bank's application if its latest version has less than five reviews in the iTunes App Store. Virtually all banks that have an application in the Android app store also have one in the iTunes app store so that this filter is comprehensive.

My main measure of digital banking is an indicator variable at the bank-year level that tracks whether the bank has a mobile application at the start of that year. Throughout my analysis I proxy for digital platforms more broadly using mobile platforms. In Appendix Section A.1, I show that this measure correlates positively with digital service provision via banks' websites.

A.2. Additional Data Sets and Sample Construction

I complement this information on banks' digital platform adoption with several additional datasets, which I describe and summarize in detail in Appendix Section A.1.

I obtain banks' annual branch locations from the FDIC Survey of Deposits. Additionally, I hand-collect publicly available online branch reviews, obtaining 700,000 reviews for 60,000 bank branches posted on Google from 2010 through 2021.

To build annual bank-level characteristics, balance sheet variables, and controls, I collect banks' balance sheet information from the FFIEC Consolidated Reports of Condition and

[6]iTunes Search API: link

Income, generally referred to as Bank Call Reports. Additionally, I retrieve banks' uninsured deposits from the SDI. Banks' deposit rates are from RateWatch.

I obtain mortgage origination information from the Home Mortgage Disclosure Act (HMDA), and small business loan origination information from the Community Reinvestment Act (CRA) disclosure statement data. Both datasets provide information on loan quantities, the location of the borrower, and borrower characteristics. In addition, starting in 2018, HMDA data reports mortgage rates. Throughout my analysis, I focus on on-balance-sheet activity to capture lending for which bank monitoring and screening is likely to be more important. Specifically, I keep HMDA mortgages that are originated for the purpose of purchasing a home, and not sold off to any government agency during the first calendar year.

I obtain data on mobile and broadband data coverage annually by provider at the census block level in 2015 from the FCC form F477, which collects data on the coverage provided by different carriers. I retrieve additional county characteristics from the Census. From FRED I retrieve the Fed funds rate, and assets held by U.S. households in money market mutual funds and deposits by wealth percentile. In order to control for the rise of Fintech mortgage providers (Buchak et al., 2018b), I obtain county level FinTech mortgage lending shares in 2015 from the dataset provided by Fuster et al. (2019).

My data sample for reduced form analysis and structural estimation contains an unbalanced annual panel of U.S. commercial banks across the years 2010 through 2019. In structural estimation I exclude banks with less than 0.001% deposit market share or fewer than 5 branches.[7] The sample period is one in which digital platform technologies are prevalent and ends just prior to the Covid-19 pandemic.

B. Institutional Details

B.1. Digital Banking Platforms

Some details regarding banks' digital platforms may be useful to the reader, given the paucity of quantitative information available on this technology. First, I look at bank adoption trends. As Figure 1 shows, there has been a steady increase in the proportion of banks with a mobile banking application after the introduction of the iTunes and Google App stores

[7]This is standard practice in the literature, see Egan et al. (2017) and Xiao (2020). However, I set my threshold at 5 rather than 10 branches in order to include the tail of small banks, given that I am interested in the effects of digital platforms across the bank size distribution. In the motivating figures, I show longer time series for the universe of U.S. commercial banks.

in 2008, and by 2019, 60% of banks have a mobile banking application.[8] In the Appendix, I additionally decompose adoption trends by bank size in Figure A.1.

Second, I analyze the types of banking services that can be conducted via these digital platforms. I find that these platforms offer a variety of services to both deposit and loan customers, plausibly serving as a viable alternative to branch visits for many customers. I report the top features of mobile applications in Figure 2, by first tabulating the most frequently occurring tri-grams (sequences of three words) in the descriptions of banks' mobile applications and then categorizing these tri-grams into features. The features reported in my data closely align with a 2021 S&P Global survey, reproduced in Appendix Figure A.3, that asks banking customers which features available on their mobile banking applications they value most. In particular, customers can access deposit and payment services, which include the ability to check account balances, transfer money across accounts, deposit checks, review transactions, and access account statements. Similarly, they can also access loan-side services including paying bills, accessing mortgage, brokerage, credit card, and car loan accounts, and applying for a new loan. Further, customers can use the mobile applications to locate a nearby branch, schedule an appointment, and speak with customer service. Finally, some customers highlight the security features of their digital platforms. By asking what customers value, this survey sheds light on what aspects of digital banking are responsible for any resulting changes in customer demand.

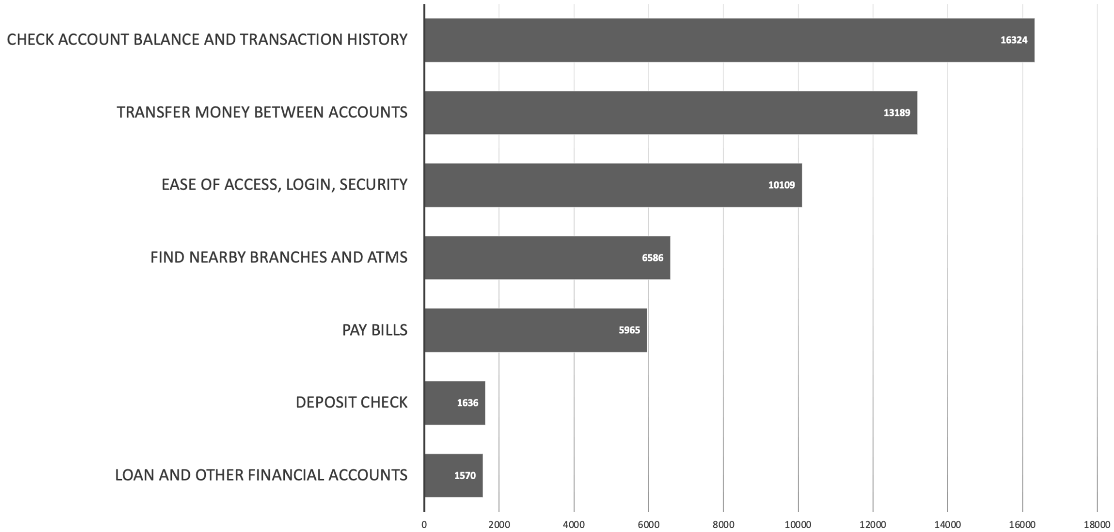
Third, the rise in importance of digital channels is also reflected in banks' communications with their shareholders. In a random sample of the annual reports of public U.S. banks in 2022, the average bank mentions their digital service platforms 10 times, counted as mentions of the words "digital", "mobile", and "online". Further, roughly 85% of banks have at least one mention of digital service platforms in their reports. Specifically, banks mention their investments in digital banking infrastructure and the performance of their digital platforms, resulting operational efficiencies and reductions in costs, and heightened competitive pressures due to digital technologies.[9]

[8] Of the remaining banks, 45% have a digital banking app with less than 5 reviews, 16% subsequently adopted a digital banking application by 2022, and 33% have no digital banking application.

[9] E.g., People's Security Bank and Trust Company (AR 2022, p.60): "Equipment related expense increased $1.1 million or 23.8 percent...due to information technology investments related to mobile/digital banking solutions". Commerce Bank (AR 2022, p.7): "Over the course of the year, we continued to invest in our digital platforms, releasing 20 updates across online and mobile banking to deliver new features and functionality". Truist Bank (AR 2022, p.6): "our mobile app had an average rating of 4.7 on Apple and Android at year-end, which is among the best in our peer group and a rapid improvement from a year ago". Capital One (AR 2022, p.35): "The ability for customers to access their accounts and conduct financial transactions using digital technology, including mobile applications, is an important aspect of the financial services industry and financial institutions are rapidly introducing new digital and other technology-driven products and services that aim to offer a better customer experience and to reduce costs.". Western Alliance (AR 2022, p.19): "Our future success depends in part upon our ability to address the needs of our customers

Figure 2. Top Mobile Banking Features

This figure shows the top categories of features that appear in the description of banks' mobile applications, sorted by frequency of occurrence. The categories are constructed by first tabulating the most frequently occurring tri-grams (sequences of three words) in the descriptions of banks' mobile applications and then grouping these tri-grams into broader categories by hand. Application data is hand-collected.



Fourth, I explore the manner by which banks invest in and develop these digital platforms. While the largest banks may develop bespoke in-house digital platforms, in their 2022 annual reports 60% of banks mention obtaining digital service technologies from third party providers.[10,11] The main providers of core banking system infrastructure — "the Big 3 in bank technology" — are FIS, Fiserv, and Jack Henry (Forbes 2021). In addition, there are also vendors that focus mainly on digital platform solutions for banks.[12] Reading the regulatory filings of these technology providers sheds light on the cost structure that banks are subject to in order to maintain digital service platforms. For instance, Fiserv's 10-K states that its "services are typically provided under a fixed or declining (tier-based) price per unit based on volume of service; however, pricing for services may also be based on minimum monthly usage fees." (2022 10-K, p.29). Thus, for the average bank the fixed costs of digital service

by using technology to provide products and services that will satisfy customer demands, as well as to create additional efficiencies in operations".

[10]The uniformity of banking platforms is also reflected in my data. As just one example, the description of over 800 mobile applications begin identically as, "Start banking wherever you are with *Application*! available to all *Bank* online banking customers, *Application* allows you to check balances, make transfers, pay bills, make deposits, and find locations."

[11]E.g. National Bank (AR 2022, p.14): "Third parties provide key components of the Company's business operations such as data processing, recording and monitoring transactions, online banking interfaces and services, internet connections and network access."

[12]A 2023 report by Verified Market Research (link) states that "The U.S. Digital Banking Platform Market is highly fragmented with the presence of a large number of players. Some of the major companies include Finastra, Backbase, Edgeverve Systems Limited, Appway, NCR Payment Solutions LLC, Alkami, Oracle, Sopra Banking Software, Lumin Digital, Deloitte Digital, FIS, and IBT Apps."

provision may include general investments in digital infrastructure and minimum monthly usage fees, whereas the marginal costs may include per-unit service fees.

Finally, I explore how banks' digital platform quality varies across the bank size distribution. Economies of scale in these technologies may lead larger banks to invest more heavily in digital platforms, so that quality is increasing in bank size (Karshenas and Stoneman, 1993). In Figure 3 Panel A, I tabulate the types of features that each bank offers on their application, and plot banks' average number of features as a function of their log assets. I find that smaller banks tend to have fewer features on their digital platforms, while the largest banks have the most. In Appendix Figure A.4 I also report how banks' average application ratings vary as a function of bank size and find that the trend is similar to that of the number of features. These findings are consistent with digital platform quality that is increasing in bank size.

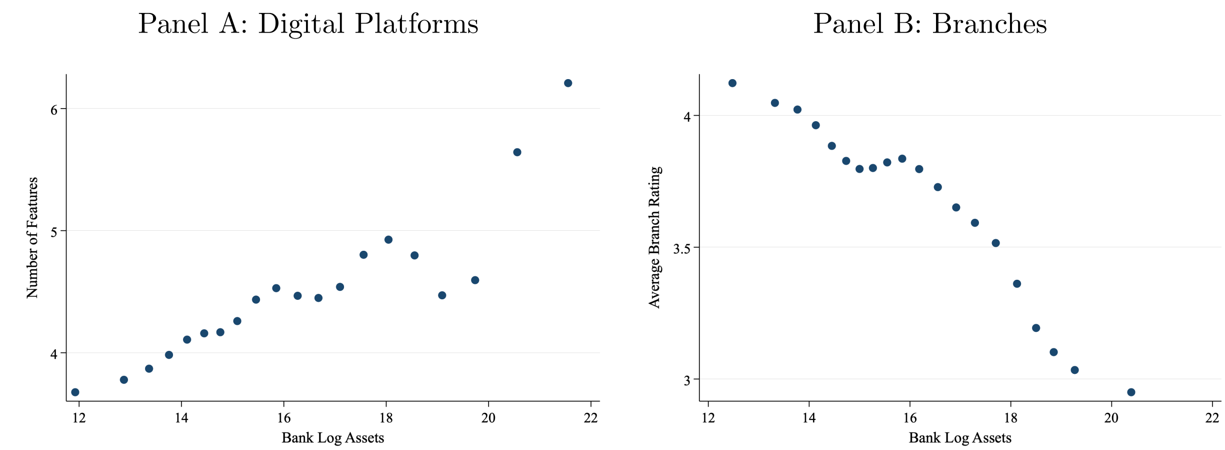
B.2. Branch Networks

The banking sector is comprised of heterogeneous banks that employ varied business models even before the development of digital technologies (Egan et al., 2022). The seminal model of Stein (2002) suggests that due to organizational synergies, large banks which have branches in more markets may naturally operate more transactional business models, whereas smaller banks focus on more relationship-intensive service provision. Further, focusing on transactional services may give rise to a more efficient ex-ante cost structure for large banks. In Figure 3 Panel B I plot a bin scatter of banks' average branch reviews as a function of their log assets, again including a county fixed effect. I find a strong negative relationship, consistent with larger banks having lower quality branches or operating a lower cost business model.

These institutional details have opposing implications for how the effects of digital platforms will vary across the bank size distribution. Digital platform quality that is increasing in bank size suggests that effects of this new technology will be more pronounced for larger banks. In contrast, if large banks' branches are of lower quality or more transactional in nature, then smaller banks may become more attractive to customers once they can additionally offer some transactional banking services digitally. Similarly, the development of digital platforms may reduce variable costs by more for smaller banks if their branch services are of higher quality and entail higher costs. In particular, customers who have a mix of transactional and relationship-based banking needs may prefer to bank with mid-sized banks — those with relatively high quality branches and digital platforms — relative to small or large banks that excel solely in branch or digital services. I explore these countervailing forces in detail throughout the remainder of the paper.

Figure 3. Service Quality and Bank Size

Panel A plots a cross-sectional binscatter comparing banks' number of mobile application features to their asset size. Panel B instead considers banks' average branch rating. Both specifications include a county FE, comparing only banks that have a branch within the same county. Application data is hand-collected. Data on banks' asset size come from 2019 from their Call Reports, branch ratings are calculated over the entire universe of hand-collected reviews, and the number of features is constructed by categorizing text strings that appear in application descriptions.



III. Empirical Strategy

The main remaining empirical challenge is the endogeneity of digital platform adoption. In this section I describe my identification strategy to circumvent this issue. Specifically, In Section III.A, I construct a novel instrument for bank digital platform adoption using cross-sectional variation in banks' exposure to technology that facilitates the development of these digital platforms. In Section III.B, I introduce my reduced form regression specification. In Section III.C, I discuss instrument validity and address several threats to identification.

A. Instrument Construction

Equation (1) describes the main relationship of interest in my reduced-form analysis.

$$Y_{b,t} = \beta\,\mathrm{Digital}_{b,t} + \gamma\,X_{b,t} + \varepsilon_{b,t} \tag{1}$$

$Y_{b,t}$ is an outcome variable at the *b*ank level, such as bank asset growth, number of markets, or ratio of uninsured deposits; $\mathrm{Digital}_{b,t}$ is an indicator variable that captures whether bank b has a digital platform by the beginning of year t; and $X_{b,t}$ is a set of control variables.

Importantly, technology adoption $\mathrm{Digital}_{b,t}$ is a choice variable of each bank b and depends on factors such as bank b's productivity, customer base, and business model, which also affect the outcomes of interest $Y_{b,t}$. As a result, all of these characteristics are included in $X_{b,t}$ in order to identify β, which is the effect of $\text{Digital}_{b,t}$ on $Y_{b,t}$ holding all else equal. The inability to empirically measure all the components of $X_{b,t}$ gives rise to a classic omitted variables bias: the key identification challenge is that $\text{Digital}_{b,t}$ is endogenous — it is correlated with the error term in an OLS regression where some elements of $X_{b,t}$ are unobservable and excluded.

I use an instrumental variables identification strategy to overcome this identification challenge. A valid instrument — one that correlates with $\text{Digital}_{b,t}$ but not with any unobservables in $X_{b,t}$ — allows me to recover an unbiased estimate of β via standard two-stage least squares (2SLS) estimation.

I construct a novel instrument Z_b for bank technology adoption $\text{Digital}_{b,t}$, using cross-sectional variation in banks' exposure to technology that facilitates the development of digital platforms. To the best of my knowledge, this is the first paper to use this variation as an instrument. In particular, one key technological advance that made digital platforms possible was the advent of smartphones and the third-party application stores that came with them. The "smartphone revolution" was catalyzed by the release of the iPhone in January of 2007. Beyond providing the hardware, Apple also simplified the development and distribution of digital banking platforms when it opened iTunes App Store in July of 2008. The iPhone and the iTunes App Store together constituted a major technological advancement that spurred the adoption of a new digital alternative to traditional commercial bank service provision via brick-and-mortar branches.[13,14]

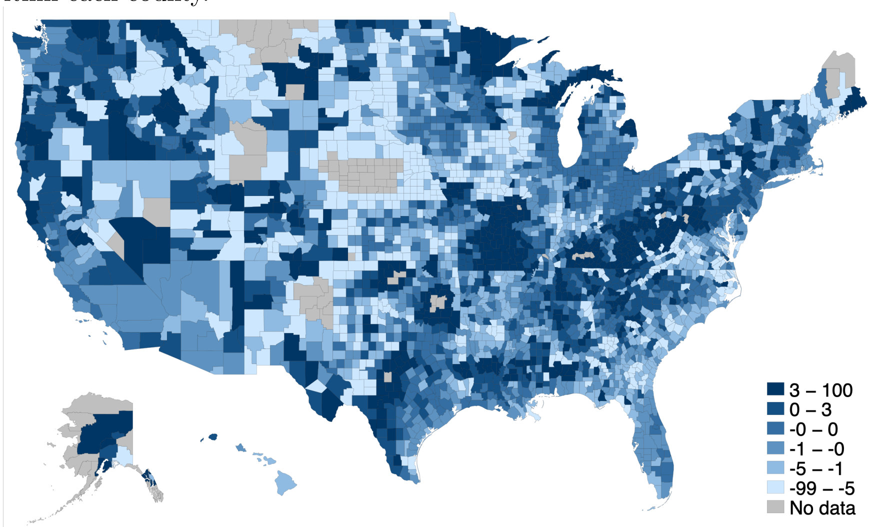
Importantly, AT&T was the sole carrier of iPhones between 2007 and 2012. This arrangement was not Jobs' first choice, as Vogelstein (2013) reports: "In 2005 Verizon had been so convinced of its dominance in the wireless business that it had turned down Jobs's offer of a partnership to build the iPhone. AT&T had been Apple's second choice". As a result, I argue that the choice of carrier between AT&T and Verizon for iPhones was determined as good as randomly with respect to the banking sector. The quasi-random availability of iPhones in markets with better AT&T coverage relative to Verizon coverage provides variation in technology that is independent of local market characteristics that determine cellular coverage in general. Indeed, both AT&T and Verizon can trace their origins to one of the seven "Baby Bells" that were created following *United States v. AT&T*, the 1974 Depart-

[13] Although the Android operating system led by Samsung smartphones later increased in capability and popularity, in early years the iPhone dominated the smartphone industry in the United States. See Appendix A.3 for more discussion.

[14] Banking websites existed prior to the development of mobile application technologies. Prior to the development of the internet, banking by mail and phone banking existed as alternatives to in-person banking. However, none of these alternatives had the revolutionary impact that mobile services have had on the banking industry. In FDIC national surveys over the past decade, telphone banking is reported to be the main method of banking for less than 4% of households (link). In my analysis, I proxy for digital platforms broadly with mobile platform adoption, given synergies in the development of these technologies.

Figure 4. Geographic Variation in Cellular Provider Coverage

This figure shows county-level proportional differences in AT&T and Verizon LTE coverage, defined to be $(ATT - Verizon)/Verizon \cdot 100$. Darker colors correspond to higher AT&T coverage relative to Verizon coverage. Coverage data at the provider-level come from FCC form F477 in 2015, and are averaged across census blocks within each county.



ment of Justice lawsuit which broke up the monopoly of Bell Labs (see map in Appendix Figure A.6). The company known as AT&T today was originally the Southwestern Bell Corporation, while Verizon was Bell Atlantic. Subsequently, both carriers grew through a series of acquisitions resulting in a roughly equal share of population-weighted spectrum, which is allocated to cellular providers through FCC auctions.[15] Thus, variation in AT&T and Verizon coverage arises as the outcome of a complex series of mergers in the cellular industry, which I argue are idiosyncratic in nature.

Through this variation, banks are heterogeneously exposed to the share of their existing customers that have access to high-quality smartphones via mobile carriers, and therefore to the technology shock that facilitates banks' provision of digital banking services. Banks in areas with higher AT&T coverage are exposed to five additional years of customer iPhone penetration, and thus likely begin to think about costly investments in digital platform technology earlier than their counterparts in areas with lower AT&T coverage. The variation in treatment exposure in the cross-section of banks provides an avenue for identification. I utilize geographic differences in AT&T's mobile data coverage relative to that of Verizon, as shown in Figure 4, to generate cross-sectional variation in the ability of banks to offer digital platforms to their consumers. I do so by constructing two variables which capture bank-level exposure to AT&T coverage and overall coverage respectively and including both

[15] Source: (link)

measures in each regression specification, where the bank-level exposure to AT&T coverage serves as my instrument Z_b, and overall cellular coverage as the key control.

Specifically, the instrument Z_b for a bank's adoption of mobile services is defined in Equations (2) through (4).

$$Z_b \equiv \sum_c \text{Shares}_{b,c} \cdot \text{Shocks}_c \tag{2}$$

$$\text{Shocks}_c \equiv \text{AT\&T}_c \tag{3}$$

$$\text{Shares}_{b,c} \equiv \frac{\text{Deposit Share}_{b,c} \cdot \text{Population}_c}{\sum_c \text{Deposit Share}_{b,c} \cdot \text{Population}_c} \tag{4}$$

Z_b is shift-share instrument for technology adoption. Shocks_c in (3) is the county c AT&T coverage. It varies from 0 to 1 and it is constructed by taking the average coverage of all census blocks within a county. For instance, if $\text{Shocks}_c = .25$, it means that 25% of the geographic area of the county is covered by AT&T. $\text{Deposit Share}_{b,c}$ is the the share of the deposits in county c issued by bank b. The numerator of $\text{Shares}_{b,c}$ in (4) is then the deposit market share of bank b in county c scaled by the population in that county. The denominator is the sum of this quantity for bank b across all counties c. $\text{Shares}_{b,c}$ approximates the proportion of bank b's deposit customers that reside in county c. Thus, Z_b captures the average AT&T coverage of bank b's existing deposit customers across all counties c.

During my sample period of 2010 through 2019, the instrument does not have a time component, and identification comes from the cross-section of banks. Deposit shares and population are measured in 2009, in the early stages of the digital revolution, as is standard in shift-share identification strategies (see Goldsmith-Pinkham et al. (2020)). AT&T coverage is measured in 2015, which is the first year the FCC collected form F477 at the provider level. I formalize the assumptions for instrument validity at the end of this section, after introducing the regression specification.

B. Reduced Form Specifications

B.1. Bank-Level Specification

I consider a 2SLS specification for my main reduced form analysis.

$$\text{Digital}_{b,t} = \delta_1 Z_b + \delta_2 \text{Coverage}_b + \delta_3 X_{b,t} + \eta_{b,t} \tag{5}$$

$$\text{Y}_{b,t} = \beta_1 \widehat{\text{Digital}}_{b,t} + \beta_2 \text{Coverage}_b + \beta_3 X_{b,t} + \varepsilon_{b,t} \tag{6}$$

Equation (5) is the first stage and (6) is the second stage; β_1 is the parameter of interest, and $X_{b,t}$ is a vector of control variables. $X_{b,t}$ includes the lag of the dependent variable and a year fixed effect, so that parameters are identified using cross-sectional variation. Coverage_b is the main control variable. The construction of Coverage_b is identical to that of Z_b, except that the shocks are the sum of both AT&T and Verizon coverage of each county rather than only AT&T. This Coverage_b variable proxies for both observable and unobservable county characteristics that may drive cellular carriers to provide service in a county, and that also correlate with our bank-level outcomes of interest.

B.2. Bank Heterogeneity Specification

In order to explore heterogeneous effects across the bank size distribution, I consider a specification in which I interact adoption with indicators for bank asset size categories. Specifically, I categorize banks into those larger than \$100 billion, between \$100 billion and \$10 billion, and the banks below \$10 billion, using a categorical variable $\text{Size}_{b,t}$. These size thresholds are based on regulatory asset thresholds: banks with over \$100B in assets are classified as category IV or higher and are subject to additional regulations, whereas banks with under \$10B in assets are classified as community banks.[16]

Thus the 2SLS specification becomes,

$$\text{Digital}_{b,t} = \delta_1 Z_b \cdot \text{Size}_{b,t} + \delta_2 \text{Coverage}_b + \delta_3 X_{b,t} + \eta_{b,t} \tag{7}$$

$$\text{Y}^{\text{Growth}}_{b,t} = \beta_1 \widehat{\text{Digital}}_{b,t} \cdot \text{Size}_{b,t} + \beta_2 \text{Coverage}_b + \beta_3 X_{b,t} + \varepsilon_{b,t}. \tag{8}$$

B.3. Bank-County Specification

In order to examine county-level outcomes, I additionally consider a bank-county level version of my specification with a "leave-one-out" version of my adoption instrument, Z_{bc}. In this case, the construction of the instrument becomes as in Equations (9) through (11), where I exclude information about county c in the construction of the shock to bank b in county c. The construction of the instrument in this case is such that the effect of interest in county c is driven by the exposure that bank b has to AT&T coverage in counties *other*

[16] Source: (link).

than c.

$$Z_{bc} \equiv \sum_{c' \neq c} \text{Shares}_{b,c'} \cdot \text{Shocks}_{c'} \tag{9}$$

$$\text{Shocks}'_c \equiv \text{AT\&T}_{c'} \tag{10}$$

$$\text{Shares}_{b,c'} \equiv \frac{\text{Deposit Share}_{b,c'} \cdot \text{Population}_{c'}}{\sum_c \text{Deposit Share}_{b,c'} \cdot \text{Population}_{c'}} \tag{11}$$

Using this bank-county specific cross-sectional shifter of technology adoption, I consider a 2SLS specification, as in Equations (12) and (13) below, for my bank-county level specifications. In this case, I replace the year fixed effect in $X_{b,c,t}$ with a county-year fixed effect.

$$\text{Digital}_{b,c,t} = \delta_1 Z_{b,c} + \delta_2 \text{Coverage}_{b,c} + \delta_3 X_{b,c,t} + \eta_{b,c,t} \tag{12}$$

$$\text{Y}_{b,c,t} = \beta_1 \widehat{\text{Digital}}_{b,c,t} + \beta_2 \text{Coverage}_{c,b} + \beta_3 X_{b,c,t} + \varepsilon_{b,c,t} \tag{13}$$

C. Instrument Validity

Instrument validity hinges on the standard relevance and exclusion restrictions of instrumental variables. Intuitively, the relevance condition requires that if a bank observes that more of its existing customers have access to technology that facilitates the use of digital platforms, this should induce the bank to invest in developing digital platforms. Formally, the instrument Z_b should be correlated with the endogenous variable of interest, $\text{Digital}_{b,t}$, after conditioning on the other control variables, notably the year fixed effects and bank b's overall cellular coverage, Coverage_b. In support of this, Table 1 reports this first stage regression of banks' adoption decision on Z_b. Column (1) shows that AT&T coverage is a strong determinant of bank adoption at the bank-year level, with the average bank being 57% more likely to adopt a digital platform in a given year if its markets go from zero to full AT&T coverage. The F-stats associated with this first stage, as well as those associated with the IV regressions in the subsequent section, pass the Stock and Yogo (2005) threshold for weak instruments.

The second assumption – the exclusion restriction – requires that after conditioning on controls, the instrument, Z_b, is uncorrelated with unobservable controls within $X_{b,t}$ in the relationship of interest, Equation 1. Goldsmith-Pinkham et al. (2020) show that the exclusion restriction for shift-share instruments is satisfied if the shares in Equation (4) are exogenous, in other words if a bank's shares in markets with high or low AT&T coverage are exogenous conditional on the bank's overall cellular coverage. For my purposes, the exogeneity of shares requires that they are orthogonal to unobservable characteristics that affect innovations in the outcomes of interest, conditional on controls that include lags in the outcome variables. This involves two assumptions: that variation in AT&T coverage is as good as random, and that this random variation in AT&T exposure affects bank outcomes only through its effect on banks' digital platform adoption decisions. I turn to these in detail below.

C.1. Variation in AT&T coverage is as good as random

The first assumption is that after controlling for a bank's overall cellular coverage, variation in its AT&T coverage is as good as random with respect to unobservable bank characteristics. As described above, one institutional fact that supports that the differential variation is unlikely to be correlated with bank unobservables is that Steve Jobs' first choice for cellular carrier was Verizon, which turned him down (Vogelstein, 2013). The choice of carrier seems as good as random, and certainly uninformed by differential bank deposit shares or other bank characteristics.

I provide three additional pieces of support for this. First, in Appendix Table A.13 I document that bank characteristics are not significantly correlated with my instrument prior to the proliferation of digital platforms, serving as an analog of "parallel trends" within this setting.

Second, a concern may be that even after controlling for overall cellular coverage, AT&T counties differ in terms of demographics in a way that correlates with bank unobservables. To explore this, I explore the correlation of county characteristics with AT&T and Verizon coverage, including the share of the population that lives in urban areas, median income, and the proportion of the population over the age of 60 in Appendix Table A.14. I find that counties with higher AT&T coverage tend to be younger, poorer, and more urban than counties with higher Verizon coverage. It is not straightforward to argue that these demographic differences are likely to confound the effects that I observe. To assuage any remaining concerns that these demographic differences confound the effects that I observe, in Appendix Section A.3 I re-estimate the main regressions of interest including these demographic controls, and find that the results remain consistent.

Third, a concern may be that AT&T coverage correlates with the presence of nonbank fintech competitors, and that the effects I document are a response to competition from nonbank entrants. To explore this, I control for banks' exposure to fintechs, measured as their exposure to fintech mortgage lending activity across their markets in 2015 and constructed analogously to my instrument Z_b. I report regression specifications with and without this fintech control for each outcome of interest. The effect of digital platform adoption on outcomes of interest remain stable with the inclusion of the fintech control, and the first stage effect of AT&T coverage on banks' adoption probabilities remains stable as well, suggesting that non-bank competition is not driving the results.

C.2. Accounting for Direct Effect of iPhones

The second assumption is that this random variation in AT&T exposure affects bank outcomes only through its effect on the bank's digital platform adoption decision. The most salient alternate hypothesis is that counties with access to AT&T coverage and iPhone technology may grow differentially because of the iPhone itself, causing in turn changes in bank size and balance sheet composition.

To address this identification concern I take two approaches. First, whenever possible I conduct my analyses at the bank-county level as in Equation (13). Notice that for this bank-county level analyses, the inclusion of a county-year fixed effect, $\beta_{c,t}$, holds fixed the local availability of iPhones and thus rules out the threat that any differential effects that I ascribe to adoption are in fact driven by differences in the presence of iPhones in county c itself leading to differential growth or industry composition.

For bank-level outcomes where it is not feasible to consider bank-county level analyses, such as overall bank balance sheet growth and deposit composition, I instead aim to control directly for the broader effects of an "iPhone economy".[17] I include controls for measures of banks' local overall deposit and business growth. Specifically, I construct the following variable,

$$\text{Bank Average X}_{bt} = \frac{\sum_c \text{Bank Branches}_{ct} \cdot X_{ct}}{\text{Bank Branches}_t}, \tag{14}$$

in turn for overall deposits, as well as for the overall number of establishments, number of employees, and business payroll in a given county c. I use these bank-level measures to construct control variables for each regression. I find that in each case, the effect of digital platform adoption is statistically and economically significant even after the inclusion of these controls to capture the direct effects of iPhones on the local economy near the bank, and that the magnitude of the coefficient remains similar to the regression without the inclusion of these controls. This finding provides evidence that the effects are not driven by changes in the local economy due to the introduction of iPhones.

In Appendix A.3 I consider and address several additional threats to the identification strategy.

[17] This analysis requires the additional assumption that changes in the outcome of interest Y_{bt} for a given bank do not affect the local economy, so that these are not "bad controls". The fact that the remaining regression coefficients remain similar with the inclusion of these controls suggests that this is indeed the case.

IV. Reduced Form Analysis

In this section I document several motivating facts on how digital platforms alter the competitive landscape of the U.S. banking sector using my instrumental variables identification strategy. First, in Section IV.A, I show that after adopting digital platforms, banks *branchlessly* expand their service provision geographically. Further, mid-sized banks grow larger. These facts suggest that digital technology is making banking markets more integrated and national, and allows mid-sized banks to compete more effectively with the largest banks.

Second, in Section IV.B, I show that after adopting digital platforms, the composition of banks' balance sheets change. On the liability side, banks increase their ratio of uninsured deposit funding, and on the asset side, banks reduce their share of loan originations to low income borrowers. I provide evidence that the deposit market results are driven by corporations preferring digital banking, or banks finding it cheaper to serve corporate deposits digitally. For loans, I show that the results are likely due to a combination of demand and supply effects. These facts suggest that the effects of this digitalization on competition vary across the different market segments that banks serve.

A. Banking Sector Competition

A.1. Digital Banks Branchlessly Enter New Markets

Digital platforms decouple banks' service provision from physical location and are available nationwide. If banks begin to operate in new geographic areas, this may increase competition and give rise to more integrated local markets, where I define a local market to be a county. To examine this, I focus on banks' mortgage and small business loan origination activity due to availability of granular panel data on the location of their originations. Clearly, deposit competition may also drive entry, and in the following subsection (A.2) I provide evidence that digital platforms alter competition in deposit markets as well. However, analysis of local deposit markets is impeded by banks' deposit data, which are linked in an ad-hoc manner to their branch networks. In particular, banks are not required to accrue online deposits to the closest branch.[18]

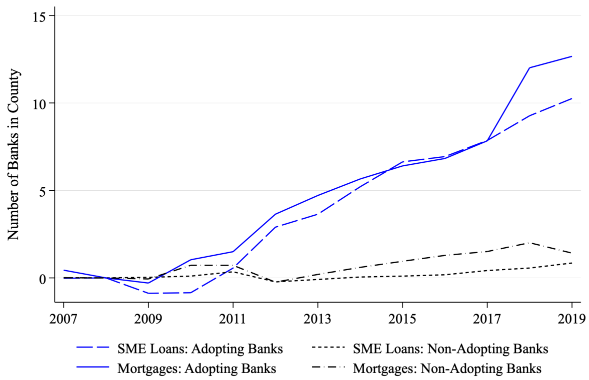
Figure 5 Panel A documents that corresponding with the rise of digital service platforms, local banking markets have experienced an increase in the average number of banks that are originating small business loans and mortgages. Strikingly, the increase in bank entry

[18]For more details on the opacity of current deposit data, see the Survey of Deposits reporting instructions (link) and a comment to the DOJ arguing that these reporting instructions should be updated to reflect digital banking (link).

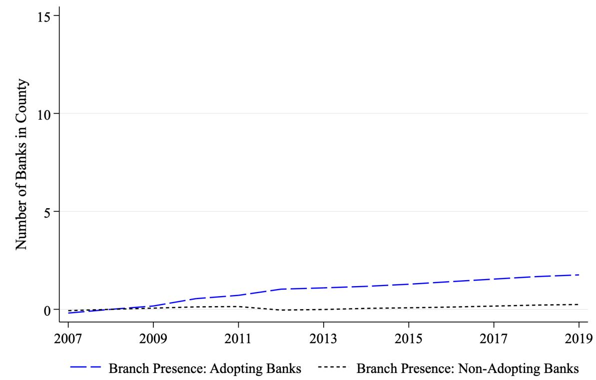
Figure 5. Number of Banks In County

Panel A shows the annual average number of banks that are originating mortgages or small business loans in a county, split depending on whether each bank adopted a digital platform. Panel B shows the annual average number of banks that have a branch in a county, split depending on whether each bank adopted a digital platform. For these figures, bank classifications are time invariant: a bank is classified to have adopted a digital platform if it did so prior to 2014. 2008 values are normalized to 0. Mortgage origination data come from HMDA. Small business loan origination data come from the CRA.

Panel A: Mortgage and Business Lending



Panel B: Branch Presence



is driven by banks that have adopted digital platforms. Further, Figure 5 Panel B shows that this expansion in bank service provision is not accompanied by a proportionate increase in bank branch presence. These trends are consistent with the notion that digital banking facilitates banks' service provision across greater geographic regions without the need to open new bank branches in these areas.

Motivated by the county-level trends, I consider an IV regression, Equation (6), for the number of local markets that banks originate mortgages in. For this regression, the dependent variable $\log(\text{Loan Counties})_{b,t}$ is the log number of counties in which bank b originates mortgages. In X_{bt} I additionally include the lagged number of markets that banks have branches in and restrict to banks that provide mortgages in at least 3 counties, in order to capture cross-sectional differences in banks' pre-existing business models. Table 2 shows that banks which adopt digital platforms increase the number of counties in which they originate mortgages by 86%.

In the Appendix, I conduct a variety of additional analyses and robustness. First, in Table A.3 I explore dynamic effects of digital platform adoption by considering leads of the outcome variable. Second, in Table A.15 I show that these results are robust to the inclusion of controls for the demographic characteristics of markets in which banks are present. Third, in Table A.19 I report OLS and difference-in-differences results.

Next, I turn to banks' branch response. First, I explore whether banks are entering or exiting counties through branch openings or closures. I consider a bank-level IV regression, Equation (6), where the dependent variable is log(Branch Counties)$_{b,t}$, the log number of counties in which bank b has branches at time t. I find in Table 3 Columns (1) and (2) that there is no significant effect on the number of counties that banks maintain branches in. Second, I examine whether banks are reducing the number of branches that they operate within a given county. I consider a bank-county level IV regression, Equation (13), where the dependent variable is log(Branches)$_{b,c,t}$, the log number of branches that bank b has in county c at time t. I find in Table 3 Column (3) that banks close 5.9% of their branches within a given county after adopting digital platforms. In the Appendix, I explore heterogeneity in branch closures depending on county characteristics in Table A.10, dynamic effects in Table A.4, and report OLS and difference-in-differences results in Table A.18.

In sum, after adopting digital platforms, banks *branchlessly* expand their service provision geographically. The branchless nature of this bank expansion differs notably from prior such developments, the most prominent of which occurred during the deregulation of bank interstate branching throughout the 1990s culminating with the Riegle-Neal Act in 1994.[19] This evidence suggests that digital platform technologies are increasing the geographic scope of bank competition.

A.2. Mid-Sized Digital Banks Exhibit Fastest Growth

While new entry into local banking markets suggests a more competitive banking sector, in order to understand how the national landscape is changing it is important to explore whether this is driven by the largest banks gaining additional market share in new geographic regions or if these changes are accompanied by the growth of smaller banks.

Indeed, there may be heterogeneous effects across the bank size distribution through two main economic channels, as detailed in Section II. First, Figure 3 Panel A documents that due to economies of scale in digital technologies, banks' digital platform quality is increasing in bank size, suggesting that effects of this new technology will be more pronounced for larger banks. Second, Figure 3 Panel B provides evidence that large banks' branches are of lower quality or more transactional in nature, so that smaller banks may become more attractive to customers, or operate more efficiently, once they can additionally offer some transactional banking services digitally. In particular, customers who have a mix of transactional and relationship-based banking needs may prefer to bank with mid-sized banks — those with relatively high quality branches and digital platforms — relative to small or large banks that excel solely in branch or digital services.

[19] My findings are complementary to prior literature that finds that advancements in information technologies more broadly expand banks' geographic scope (Petersen and Rajan, 2002, Berger and DeYoung, 2006, Jiang et al., 2022).

To this end, I explore the effect of digital platform adoption on bank growth across the bank size distribution. I measure growth, in either assets or deposits, using the centered growth rate, which is standard in analyses of firm dynamics:

$$\mathrm{Y}_{b,t}^{\text{Growth}} = \frac{Y_t - Y_{t-1}}{.5(Y_t + Y_{t-1})}.$$

I consider a bank-level IV regression that allows for heterogeneous effects across the bank size distribution, Equation 8, where the dependent variable is banks' growth in assets or deposits. Table 4 shows that the effects on bank growth follow an inverse-U shape across the bank size distribution: only mid-sized banks with between \$10 and \$100 billion dollars in assets grow differentially after adopting digital platforms, growing between 3-4% faster than other banks. These results are consistent with the economic channels described above, whereby the demand or supply effects of the smallest banks are attenuated due to digital platforms of lower quality, and the demand or supply effects of the largest banks are dampened due to their ex-ante business models already operating more similarly to digital platforms.

It is of interest to understand whether digitalization changes bank competition in deposit or loan markets. The evidence in the prior subsection on banks' geographic expansion to originate loans provides evidence that digital platforms alter banks' competition in loan markets. To explore whether digital platforms are additionally altering competition in deposit markets, I consider a specification in Table 4 Column (7) where I control for the change in banks' centered loan growth. I find that the deposit growth of mid-sized digital banks remains significantly elevated even after controlling for changes in loan growth. This provides evidence that digitalization alters bank competition in both deposit and loan markets independently.

In the Appendix, I conduct a variety of additional analyses and robustness. First, in Table A.5 I report the result for average bank growth following digital platform adoption as in Equation (6). Second, in Table A.6 I explore dynamic effects of digital platform adoption by considering leads of the outcome variable. Third, in Table A.16 I show that the results are robust to the inclusion of controls for the demographic characteristics of markets in which banks are present. Fourth, in Table A.20 I report OLS and difference-in-differences results.

B. Unequal Effects on Competition Across Banking Market Segments

While the evidence thus far suggests that digital platforms make the banking sector more competitive, the extent to which it does so may differ across different banking products. If digital banking disproportionately leads to the growth of certain market segments, then it may lead to changes in banks balance sheet composition, which I explore in this section.

B.1. Digital Banking Facilitates Uninsured Deposits

First, I explore whether there are heterogeneous effects across different deposit products. In particular, I consider insured and uninsured deposit markets. This choice is motivated by the possible differences in demands and costs across these depositors as a result of digital banking platforms, as well as the resulting financial stability implications if there are differential effects. While insured deposits are largely comprised of retail deposits, uninsured deposits include corporate deposits. It could be that corporations disproportionately prefer to manage their finances and payroll digitally, so that there is an inflow of uninsured deposits to digital banks. On the other hand, there may be an inflow of insured deposits if digital platforms disproportionately reduce the costs of providing retail deposits. Further, banks' funding composition across these deposit market segments has implications for bank funding stability due to the heightened interest rate and risk sensitivity of uninsured deposits, as seen during the 2023 banking crisis (Egan et al., 2017, Jiang et al., 2023, Drechsler et al., 2023).

I define bank b's Insured Deposit Ratio$_{bt}$ in year t as follows.

$$\text{Insured Deposit Ratio}_{bt} = \frac{\text{Insured Deposits}_{bt}}{\text{Deposits}_{bt}}$$

Table 5 reports the results of a bank-level IV regression that allows for heterogeneous effects across the bank size distribution, Equation 8, where the outcome variable is the log of banks' insured deposit ratio. I find that the growth in deposits among adopters is disproportionately driven by uninsured deposits: the insured deposit ratio among large and mid-sized digital banks decreases by around 2%. This suggests that digital platforms disproportionately facilitate the provision of uninsured deposits, with implications for banks' funding stability.

While I leave disentangling the demand and cost-side channels for the structural model, I am able to provide some evidence that it is indeed corporate deposits that flow to banks with digital platforms. Anecdotally, industry reports state that "a strong digital treasury platform is now table stakes to grow commercial deposits".[20] In my data, I consider the following IV specification,

$$Y_{b,t} = \beta_1 \widehat{\text{Digital}}_{b,t} \cdot \text{Business Payroll}_{b,t-1} + \beta_2 \text{Business Payroll}_{b,t-1} + \beta_5 X_{b,t} + \varepsilon_{b,t} \tag{15}$$

[20] Cornerstone Advisors, "What's Going on in Banking" 2023 Report (link).

where Business Payroll$_{b,t-1}$ is the log of the overall local business payroll in banks' markets in year $t-1$, $Y_{b,t}$ is again the banks' insured deposit ratio, and $X_{b,t}$ additionally includes a bank fixed effect. In Table 6, I find that the coefficient β_1 is negative and statistically significant, so that banks' uninsured deposit ratio increases by more if they adopt digital platforms and are located in areas with more corporate payroll, and thus likely higher corporate deposits.

In the Appendix, I conduct a variety of additional analyses and robustness. First in Table A.7 I report the result for average bank insured deposit ratio following digital platform adoption as in Equation (6). Second, I explore dynamic effects of digital adoption by considering leads of the outcome variable in Table A.8. Third, I show that the results are robust to the inclusion of controls for the demographic characteristics of markets in which banks are present in Table A.17. Fourth, I report OLS and difference-in-differences results in Table A.25.

B.2. Digital Banking Facilitates Loans to High Income Borrowers

I next explore whether there are differences in the effects of digital banking platforms across loan markets. These could arise due to differences in loan customer preferences or ability to apply for a loan via a branch visit versus digitally. Alternatively, banks may find it easier to screen or monitor certain loan customers digitally.

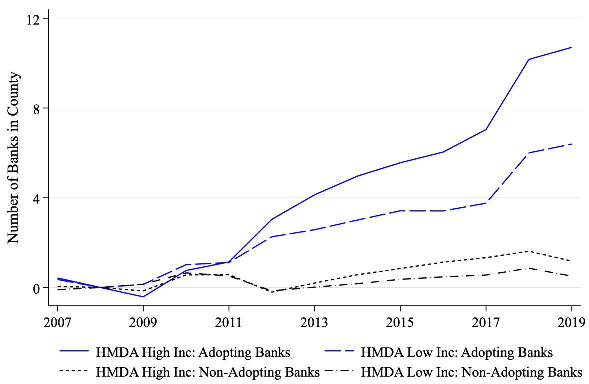
One key dimension along which effects may vary is borrower income, which can be viewed as a proxy for the extent to which intangible information is important. On average, lower income borrowers are less able to satisfy lending thresholds based on codifiable information, which require relatively higher credit scores, wealth, collateral, down-payments, or income. It may be that digital platforms facilitate the provision of loans that rely less on intangible information, given the large literature on banks' use of transactional and intangible information and the importance of physical proximity for developing banking relationships and collecting intangible information (e.g. Petersen and Rajan (2002), Liberti and Petersen (2019)). On the other hand, there is a recent literature documenting that fintech expands credit access for lower income borrowers, and thus it could be that banks actually supply more credit to these borrowers after adopting digital platforms (E.g., Erel and Liebersohn (2022), Degerli and Wang (2022)). I classify a loan to be *low income* if the loan borrower has low or moderate income according to the FFIEC, i.e. those borrowers that have income below or equal to 80% of median family income for a given market, and *high income* otherwise.

To begin, I explore whether bank geographic expansion into new markets varies depending on the income of the borrower. In Figure 6, I decompose Figure 5 by looking at banks' average mortgage and small business loan origination activity in a market over time, split by the

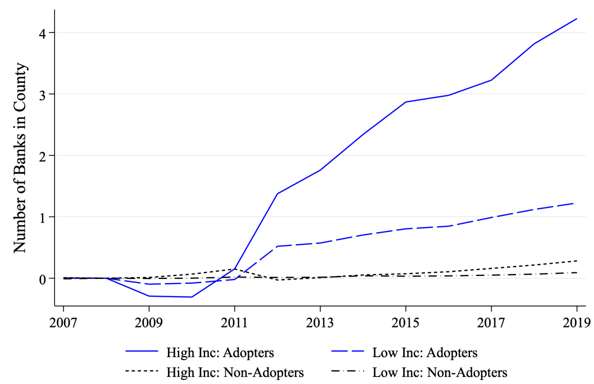
Figure 6. Number of Banks In County: Heterogeneity

Panel A shows the annual average number of banks that are originating mortgages in a county, split depending on whether the borrower of the mortgage is high or low income, and additionally depending on whether each bank adopted a digital platform. Panel B repeats the exercise for small business loan originations. For these figures, bank classifications are time invariant: a bank is classified to have adopted a digital platform if it did so prior to 2014. A borrower is classified to be low income if their income is below 80% of the median MSA family income, and high income otherwise. 2008 values are normalized to 0. Mortgage origination data come from HMDA. Small business loan origination data come from the CRA.

Panel A: Mortgages



Panel B: Business Loans



income of the borrower. The results are striking: bank expansion into new counties is driven overwhelmingly by loan originations to high income borrowers rather than to low income borrowers. This is consistent with the notion that these low income borrowers may not apply for loans digitally or may require more in-person intangible information acquisition by the bank in order to make profitable lending decisions. I next consider a bank-level IV regression of adopting banks' expansion split by income in Table 2 columns (2) and (3). For these regressions, the dependent variable log(Loan Counties)$_{b,t-1}$ is the number of counties in which bank b originates at least one high or low income mortgage respectively. In Column (2) I find that banks increase the number of counties in which they provide mortgages to high income borrowers by 124%. In contrast, Column (3) documents that for low income borrowers, this increase is only by 53%.

Next, I look at whether this uneven geographic expansion also translates into a change in the composition of loans that banks originate in the counties that they enter. I define Low Income Ratio$_{bt}$ as below, both for the number of mortgages as well as the dollar volume of mortgages originated.

$$\text{Low Income Ratio}_{bt} = \frac{\text{Low Income Mortgage Origination}_{bt}}{\text{Mortgage Origination}_{bt}}$$

Table 7 Columns (1) and (2) report the results of a bank-county level IV regression, Equation 13, for the log of banks' low-income mortgage origination share measured in terms of the number and dollar volume of mortgages respectively. I restrict the sample to counties c in which bank b has no branches in year t, and in X_{bct} I additionally include the lagged number of markets that banks have branches in, in order to capture cross-sectional differences in banks' pre-existing business models. I find that adopting banks reduce their local low-income mortgage origination ratio by 27% in terms of the number of mortgages, and 38% in terms of the dollar volume of mortgages originated.

Notably, during my time period of analysis, non-bank lenders (including fintech lenders such as Quicken Loans) have become a significant player in mortgage markets, and it is of interest to understand whether any of these documented effects are due to competition from these new entrants (Buchak et al., 2018a,b). My instrument for digital platform adoption goes some way towards addressing this concern, since a banks differential out-of-market AT&T coverage should be uncorrelated with the competition they face within a given market from nonbank lenders. As an additional check, I analyze loans that banks lend in a market segment that is unaffected by non-bank competition: Jumbo mortgages. The vast majority of these mortgages remain on bank balance sheets, are not eligible for GSE support, and are difficult to securitize (Buchak et al., 2018a). Given that these are relatively high value mortgages, instead of splitting these mortgages into those made to low- versus high-income borrowers, I look at the average borrower income for these originations in Table 7 Column (3). Reassuringly, I find that after adopting digital platforms, the average income of a jumbo mortgage borrower for that bank increases, again consistent with the notion that digital banking particularly facilitates lending to high income borrowers. Thus, it does not appear that these effects are driven by securitization or fintech non-bank lender competition.

The granular nature of the HMDA mortgage data allows me to provide some reduced form evidence on whether these effects are driven by a lack of low income customer demand for loan applications via digital platforms, or due to banks' rejections of these applications. In particular, I observe loan applications and loan rejections in addition to loans that are ultimately originated. First, Column (1) of Table 8 reports the results of a bank-county level IV regression, Equation (13), for the log of banks' number of mortgage applications. Again, I restrict the sample to counties c in which bank b has no branches in year t, and in X_{bct} I additionally include the lagged number of markets that banks have branches in, in order to capture cross-sectional differences in banks' pre-existing business models. I find that banks indeed see an increase in overall local mortgage applications by 60%. Next, in Column (2) I consider an analogous regression where the dependent variable is now the log of banks' low income application ratio, where this ratio is defined in Equation (16).

$$\text{Low Income Application Ratio}_{bct} = \frac{\text{Low Income Applications}_{bct}}{\text{Applications}_{bct}} \tag{16}$$

I find that after adopting digital platforms, banks receive 26% fewer applications from low income mortgages than before, consistent with a demand-side mechanism whereby low income borrowers are less likely to apply for mortgages digitally. Finally, in Column (3) I consider a regression where the dependent variable is the log of banks' low income rejection ratio, where this ratio is defined in Equation (17).

$$\text{Low Income Rejection Ratio}_{bct} = \frac{\text{Low Income Rejections}_{bct}}{\text{Low Income Applications}_{bct}} \tag{17}$$

Banks reject 76% more of their low income mortgage applications, which provides evidence in turn that bank supply of low income mortgages changes after adopting digital platforms.

In the Appendix, I conduct a variety of additional analyses and robustness. First, in Section C I document that the growth of these on-balance-sheet mortgages to low-income borrowers has slowed in aggregate during this time period. Second, in Section D.1 I look at how the results differ for government guaranteed loans, and find that lending to low income borrowers actually increases for this market segment, consistent with the literature that shows that fintech lenders are able to expand access to government credit for traditionally under-served populations (e.g. Erel and Liebersohn (2022), Howell et al. (2021)) and suggesting that technology has different effects on lending behavior depending on whether the lenders engage in significant monitoring or screening behavior. Finally, in Section D.2 I analyze loan LTVs, in Table A.9 I explore dynamic effects, and in Table A.26 I report OLS and TWFE results.

To summarize, the fact that digital adoption leads banks to reduce their share of loan originations to low income borrowers suggests that digital platforms disproportionately facilitate the provision of loans to high income borrowers. The evidence related to banks' applications and rejections suggest that this is not fully driven by a lack of demand from low income borrowers, but that digital platforms may also affect banks' supply of low income loans. In particular, if digital platforms alter banks' ability to monitor or screen different types of loan borrowers, this has implications for the production of credit risks in the banking sector. In order to examine this, I disentangle the demand and supply-side mechanisms, including the effect on banks' monitoring or screening ability, in Section V through my model framework.

V. A Model with an Endogenous Banking Industry Structure

The reduced form evidence of Section IV shows that digitalization matters for banking, that is, for bank behavior and industry structure. Still, disentangling the specific mechanisms through which digitalization matters requires a model that allows me to identify parameters governing how digital platforms affect customer demands and bank supply. Moreover, a model is needed to quantify the aggregate effects of bank digitalization on competition, welfare, and financial stability. In Section V.A, I present the model setup and timing across the two periods, $t = 0, 1$. In Section V.B I explain customers' utility maximization decisions at $t = 1$, in Section V.C I explain banks' profit maximization at $t = 1$ via rate setting, and in V.D I explain banks' investment decisions at $t = 0$. In Section V.E I describe equilibria of the model.

A. Overview

A.1. Setup

The model features as agents banks and customers in both deposit and loan markets. Deposit markets are *national*. There are two deposit markets, insured and uninsured. Loan markets are *local*, i.e. county-specific. In each county, there are two loan markets, for high and low income borrowers.[21] Specifically, let c denote a county, and $\mathcal{C} = \{1, ...C\}$ denote the set of all counties. Let j denote a specific market, where $j \in \mathcal{J} = \{DI, DU, \{H_c\}_{c\in\mathcal{C}}\{L_c\}_{c\in\mathcal{C}}\}$. DI stands for the national insured deposit market, DU for the national uninsured deposit market, $\{H_c\}_{c\in\mathcal{C}}$ for the local high income loan markets, and $\{L_c\}_{c\in\mathcal{C}}$ for the local low income loan markets. In each market j, there are a mass of customers M^j who maximize their utilities by choosing where to obtain banking services from. Specifically, they optimally choose their portfolio allocations across the banks that are present in the market, and an outside option, on which more below in Section V.B.

A set of banks $\mathcal{B} = \{1, ...B\}$ maximize profits by providing services in these markets $\mathcal{J}$. Let N_{bc} the number of branches that bank b has in county c, and denote by $\boldsymbol{N}_b = [N_{b1}, N_{b2}, \cdots, N_{bC}]$ bank b's branch network. Let $\mathcal{C}_b = \{1, ..., C_b\}$ the set of counties in which bank b originates loans.[22] Let $\mathcal{B}_c$ denote the set of banks that are originating loans in county c, i.e. banks b

[21] These market classifications are chosen based on key product characteristics along which the effects of digital banking may differ, and for which compositional changes in bank holdings may matter for financial stability, as suggested by the reduced form analysis. I model deposit markets nationally given that digital banking leads to increasingly national competition and due to a lack of accurate data on local deposit quantities (see discussion in Section IV).

[22] Note that $\mathcal{C}_b$ need not be equal to the counties in which the bank has branches, consistent with the reduced form evidence of Section IV.

such that $c \in \mathcal{C}_b$. Let $O_b \in \{0,1\}$ denote whether or not bank b offers a digital platform. I define the banking industry as the tuple

$$\{\mathcal{C}_b, \boldsymbol{N}_b, O_b | \Theta\}_{b \in \mathcal{B}},$$

where Θ is a set of exogenous characteristics in the economy that define banks and markets. The key feature of my model is that the banking industry is endogenously determined.

A.2. Timing

The model proceeds in two stages. First, at $t = 0$, banks $b \in \mathcal{B}$ determine their branch networks $\boldsymbol{N}_b$, choose which counties $\mathcal{C}_b$ to originate loans in, and decide whether or not to adopt digital platforms O_b. Banks incur digital platform adoption costs F_O, per-branch operating costs F_N, and county entry costs F_C.

Second, at $t = 1$, these differentiated banks compete by simultaneously setting rates in each market $j \in \mathcal{J}$. In each market j, the customers M^j each choose a bank, or their outside option, to obtain banking services from in order to maximize their utility. Customers value both the availability of digital platforms and branches, and at $t = 1$ each bank b faces the following demand schedules:

$$\mathcal{Q}_b \equiv \left\{Q_b^{DI}\left(R_b^{DI}\right), Q_b^{DU}\left(R_b^{DU}\right), \left\{Q_{bc}^{H}\left(R_{bc}^{H}\right)\right\}_{c \in \mathcal{C}_b}, \left\{Q_{bc}^{L}\left(R_{bc}^{L}\right)\right\}_{c \in \mathcal{C}_b}\right\}, \tag{18}$$

where $Q_b^{DI}\left(R_b^{DI}\right)$ is the national demand schedule for insured deposits of bank b given rate R_b^{DI}, $Q_b^{DU}\left(R_b^{DU}\right)$ is the national demand schedule for uninsured deposits of bank b at rate R_b^{DU}, and $Q_{bc}^{H}\left(R_{bc}^{H}\right)$ and $Q_{bc}^{L}\left(R_{bc}^{L}\right)$ are the demand schedules for high and low income loans of bank b in local county c, respectively, at rates R_{bc}^{H} and R_{bc}^{L}. At this stage banks account for expected loan losses L, and face service provision costs Φ, which both depend on the existence of digital platforms and branches as determined at $t = 0$ by the bank.

Equilibrium is determined by market clearing via the demand schedules, which arise from the utility maximization of customers in each market j. Banks solve their optimization problem by working backwards from $t = 1$.

B. Customer Demands

B.1. National Deposit Demand Curves

I model customers' demands for each bank $b \in \mathcal{B}$ in national insured $Q_b^{DI}\left(R_b^{DI}\right)$ and uninsured $Q_b^{DU}\left(R_b^{DU}\right)$ deposit markets via a discrete choice framework. This technique is standard in the growing structural banking literature (see Dick (2008), Egan et al. (2017), Buchak et al. (2018b), Wang et al. (2020), Xiao (2020), Diamond et al. (2020) based on the methods introduced by Berry et al. (1995)). I build on this literature along one key dimension — by including and endogenizing the existence of banks' digital platforms.

Consider the national insured deposit market. Insured depositors have a total mass M^{DI}, and each depositor i in the market is endowed with \$1 that they choose to deposit in one of the banks in $\mathcal{B}$, or an outside option, which I take to be a money market fund that pays the federal funds rate f but offers no convenience benefits. Equivalently, we can think of the depositors as making a discrete choice for each dollar they they own, so that the choices aggregate to portfolio shares. Each depositor i chooses the option which maximizes their utility, given by the expression below.

$$\max_{b \in B} \quad \mu_{ib} = \underbrace{\alpha_{DI}^{R} R_b^{DI} + \alpha_{DI}^{N} N_b + \alpha_{DI}^{O,S} O_b S_b + \alpha_{DI}^{\Theta} \Theta_b + \xi_{ib}}_{\equiv \alpha_{DI} X_b} + \varepsilon_{ib} \tag{19}$$

Here, recall, O_b is a binary variable tracking whether bank b has a digital platform. N_b is bank b's number of branches. S_b is a categorical variable tracking whether bank b is a bank that has below \$10B, between \$10B and \$100B, or above \$100B in assets. Θ_b is a vector of other salient characteristics of bank b for deposit customers. ξ_{ib} is the structural disturbance, i.e. the component of bank b's quality that I do not observe as the econometrician. ε_{ib} is the idiosyncratic taste variation, which follows an extreme value distribution.

I allow the effect of digital platforms $\alpha_{DI}^{O,S}$ on depositor utility to vary by bank size, as digitalization may have heterogeneous effects on the demand faced by banks across the size distribution through two main economic channels, as detailed in Sections II and IV. First, due to economies of scale in digital technologies, banks' digital platform quality is increasing in bank size, which may lead to dampened demand effects for the smallest banks. Second, due to organizational synergies, larger banks' branches are more transactional in nature (Stein, 2002) and are present in many markets. Thus, when a larger bank offers a digital platform it may not offer a very different service relative to what is already offered through its branches, experiencing a smaller change in its customer base as a result and resulting in a dampened demand effect. The functional form in Equation (19) is able to capture the net effect of these forces.[23]

[23] In Appendix A.6 I introduce a variation of equation (19) that models these two forces explicitly and I confirm the sign of these relations. I additionally present a simple version of deposit demands, without heterogeneity across bank size.

Given this, and normalizing the utility of the outside option to 0, I can write the demand that bank b faces in the insured deposit market as

$$Q_b^{DI} = M^{DI} \cdot s_b^{DI} = M^{DI} \cdot \frac{exp(\alpha_{DI} X_b)}{1 + \sum_{b' \in \mathcal{B}} exp(\alpha_{DI} X_{b'})},$$

where s_b^{DI} denotes bank b's market share. Customer utilities and the demand that banks face in the national uninsured deposit market are derived analogously.

B.2. Local Loan Demand Curves

I model customers' demands for each bank $b \in B$ in local high income $Q_{bc}^H \left(R_{bc}^H\right)$ and low income $Q_{bc}^L \left(R_{bc}^L\right)$ loan markets again via a discrete choice framework.

Consider the high income loan market in county c. Loan customers in this market have total mass M_c^H and each customer i in the market is seeking to borrow \$1 from one of the banks that are present in county c, $b \in \mathcal{B}_c$, or an outside option. Again, we can think of the loan customers as making a discrete choice for each dollar they they wish to borrow. I take the outside option to include borrowing from non-banks as well as deciding to not take out a loan. Each customer i chooses the option which maximizes their utility,

$$\max_{b \in B_c} \quad \mu_{ibc} = \underbrace{\alpha_H^R R_{bc}^H + \alpha_H^N N_{bc} + \alpha_H^O O_b + \alpha_H^\Theta \Theta_{bc} + \xi_{ib}}_{\equiv \alpha_H X_{bc}} + \varepsilon_{ibm}$$

Here, recall, O_b is a binary variable tracking whether bank b has a digital platform, N_{bc} is bank b's number of branches in county c, and Θ_{bc} is a vector of other salient characteristics of bank b for customers in county c. ξ_{ibc} is the structural disturbance. ε_{ib} is the idiosyncratic taste variation, which follows an extreme value distribution.

Given this, and normalizing the utility of the outside option to 0, I can write the demand that bank b faces in the high income loan market in county c as

$$Q_{bc}^H = M_c^H \cdot s_{bc}^H = M_c^H \cdot \frac{exp(\alpha_H X_{bc})}{1 + \sum_{b' \in \mathcal{B}_c} exp(\alpha_H X_{b'c})}$$

where s_{bc}^H denotes bank b's market share. Customer utilities and the demand that banks face in county c for low income loans is derived analogously.

C. Banks' Profit Maximization at $t = 1$

Each bank $b \in \mathcal{B}$ maximizes profits at $t = 1$, π_b, by setting rates in each market j given the demand curves that it faces. At this stage, all investment decisions have already been determined, so the bank takes its digital platforms, branch network, and counties where it provides services as given. Bank b's profit at this stage is given by,

$$\begin{aligned}\max_{R^{DI},R^{DU},\{R_c^H\},\{R_c^L\}} \pi_b =& \pi_b(R_b^{DI}, R_b^{DU}, \{R_{bc}^H\}_{c\in\mathcal{C}_b}, \{R_{bc}^L\}_{c\in\mathcal{C}_b}) = \\ & \underbrace{\sum_{c\in\mathcal{C}_b}(R_{bc}^H - f)Q_{bc}^H(R_{bc}^H) + \sum_{c\in\mathcal{C}_b}(R_{bc}^L - f)Q_{bc}^L(R_{bc}^L)}_{\text{Local loan return}} \\ & + \underbrace{(f - R_b^{DI})Q_b^{DI}(R_b^{DI}) + (f - R_b^{DU})Q_b^{DU}(R_b^{DU})}_{\text{National deposit return}} - \underbrace{L_b(\mathcal{Q}_b)}_{\text{Losses}} - \underbrace{\Phi_b(\mathcal{Q}_b)}_{\text{Costs}},\end{aligned} \tag{20}$$

where, recall, $\mathcal{Q}_b$ is the set of demand schedules that bank b faces, as given in Equation (18), and f is the Fed funds rate.[24] The bank must account for expected loan losses L on its loan originations, and faces variable service provision costs Φ on its deposits and loan originations. The demand schedules $\mathcal{Q}_b$, the expected loan losses L, and the service provision costs Φ that the bank faces depend on the banks' branch network and digital platforms which are determined at $t = 0$.

C.1. Expected Loan Losses

Banks take on credit risk as they underwrite loans, which results in expected losses, L. Banks can manage these losses through screening or monitoring their borrowers in order to alleviate information asymmetries in these credit markets. I allow for branches and digital platforms to alter banks' monitoring or screening ability, and thereby affect expected loan losses, and for their efficacy to vary across low and high income loan markets. I develop a reduced-form parameterization of expected loan losses from a micro-foundation of banks' costly monitoring or screening, based on the seminal work of Leland and Pyle (1977) and Diamond (1984).

Consider a bank b that lends \$1 at rate R_a to a borrower of type $a \in \{H, L\}$ in a county c that has initial wealth $\omega = 0$ and access to a risky investment opportunity which returns $\tilde{y} \in \{0, y\}$ for $y \geq R_a$.

The probability of loan default is determined by a variety of factors. The baseline probability of loan default is determined by the specific bank b. Let this baseline probability be p_b. The bank further has access to two types of information technologies, branches and digital platforms. They alter the probability of a client's default either via affecting banks' ability to monitor (inducing the borrower to exert effort) or screen (by selecting borrowers of

[24] In Appendix section A.4 , I describe banks' balance sheet and derive this profit maximization.

higher credit quality). Thus, if the bank opts to invest in a single branch, it further alters the probability of default by a factor $\delta^N + \delta_a^N$, where the last term captures variation in the effect of branch monitoring or screening across borrower type. In this case the new probability that the investment yields 0 becomes $p_b + \delta^N + \delta_a^N$. Similarly, if the bank opts to invest in a digital platform O, the new probability that the investment yields 0 becomes $p_b + \delta^O + \delta_a^O$. Notice that once again I allow for the possibility that digital platforms O have a different efficacy in monitoring high income borrowers H than they do low income borrowers L.

The bank can of course invest in multiple branches N and moreover use both branches N and digital platforms O. In this case, the probability of failure becomes $p_b + \delta^O + \delta_a^O + \delta^N N + \delta_a^N N$. Thus, the expected loss L_{bc}^a for lending to borrower a for bank b in county c is given by,

$$L_{bc}^a = p_b + \delta^N N_{bc} + \delta_a^N N_{bc} + \delta^O O_b + \delta_a^O O_b,$$

where N_{bc} is the number of branches that bank b has in county c, and O_b is an indicator variable denoting whether the bank invested in digital platform technology.

Now, suppose that the bank makes Q_{bc}^L loans to borrowers of type $a = L$ and Q_{bc}^H loans to borrowers of type $a = H$ in a county c. The expected loss $L_{bc}(Q_{bc}^L, Q_{bc}^H)$ for bank b's overall lending in county c is given by the following equation.

$$L_{bc}(Q_{bc}^L, Q_{bc}^H) = L_{bc}^L \cdot Q_{bc}^L + L_{bc}^H \cdot Q_{bc}^H \tag{21}$$

I take Equation (21) to be my parameterization of bank b's expected loan losses from county c, and I let expected loan losses be additive across bank b's counties $c \in \mathcal{C}_b$,

$$L_b(\mathcal{Q}_b) = \sum_{c \in \mathcal{C}_b} L_{bc}(Q_{bc}^L, Q_{bc}^H). \tag{22}$$

C.2. Service Costs

Informed by the evidence in Section IV, I specify service cost functions that are flexible enough to identify how digital platforms affect variable costs across different market segments and across the bank size distribution.

For deposit market costs, as with demand (see Section V.B), I allow the costs functions to vary across the bank size distribution, as the evidence in Sections II and IV suggests may be the case. Specifically, large banks may have more efficient business models even in the absence of digital platforms, so that the effect of digital platforms on their variable cost structure is less pronounced. Similarly, small banks may have digital platforms of lower quality, so that the effect of digital platforms on their variable costs is lower. I model digital platforms and branches to alter the slope of marginal costs with respect to quantities. Specifically, the marginal deposit service cost in market $j \in \{DI, DU\}$ is,

$$\frac{\partial \Phi_b^j}{\partial Q_b^j} = \phi_j^N N_{bt} Q_b^j + \phi_j^{Q,S} Q_b^j S_b + \phi_j^{O,S} O_b Q_b^j S_b + \phi_j^{\Theta} \Theta_b + \xi_b^j, \tag{23}$$

where Q_b^j is the quantity of insured or uninsured deposits that bank b provides, O_b is a binary variable tracking whether bank b has a digital platform, N_b is bank b's number of branches, S_b is a categorical variable tracking whether bank b has below \$10B, between \$10B and \$100B, or above \$100B in assets, Θ_b is a vector of controls capturing bank b's baseline cost differences, and ξ_b^j is the structural disturbance to bank b's marginal service costs in market j.

While deposit markets are national, loan markets are local at the county-level. Accordingly, I consider a parsimonious parameterization of bank b's marginal loan market costs in market $j \in \{H, L\}$ and county $c \in \mathcal{C}_b$ to be a linear function of digital platforms, branches, and county characteristics,

$$\frac{\partial \Phi_{bc}^j}{\partial Q_{bc}^j} = \phi_j^N N_{bc} + \phi_j^O O_b + \phi_j^{\Theta} \Theta_{bc} + \xi_{bc}^j, \tag{24}$$

where O_{bt} is a binary variable tracking whether bank b has a digital platform, N_{bc} is bank b's number of branches in county c, Θ_{bc} is a vector of controls capturing bank b's baseline cost differences in county c, and ξ_b^j is the structural disturbance to bank b's marginal service costs in market j and county c.

Costs are additive across market segments. For bank b, the total service cost, Φ_b, (see Equation (20)) is then,

$$\Phi_b(\mathcal{Q}_b) = \Phi_b^{DI}(Q_b^{DI}) + \Phi_b^{DU}(Q_b^{DU}) + \sum_{c \in \mathcal{C}_b} \Phi_b^L(Q_c^L) + \sum_{c \in \mathcal{C}_b} \Phi_b^H(Q_c^H).$$

D. Banks' Investment Stage $t = 0$

At $t = 0$, banks $b \in \mathcal{B}$ determine their branch networks $\boldsymbol{N}_b$, choose which counties $\mathcal{C}_b$ to originate loans in, and decide whether or not to adopt digital platforms O_b, in order to maximize their overall profit, Π_b,

$$\max_{O_b, \boldsymbol{N}_b, \mathcal{C}_b} \Pi_b = \underbrace{\pi_b[O_b, \boldsymbol{N}_b, \mathcal{C}_b]}_{t=1 \text{ Profits}} - \underbrace{F_O(O_b)}_{\text{Adoption Cost}} - \underbrace{F_N(\boldsymbol{N}_b)}_{\text{Branch Maintenance}} - \underbrace{F_C(\mathcal{C}_b)}_{\text{Entry Cost}}, \tag{25}$$

where banks incur digital platform adoption costs F_O, per-branch maintenance costs F_N, and county entry costs F_C.

D.1. Adoption Cost

The bank pays a cost to adopt digital service platforms, as motivated in Section II. I model these costs as in Equation (26) to be concave in bank balance sheet size. This parsimonious parameterization captures that investments in digital platforms cost more when a bank serves more customers, but that the costs increase less than linearly with bank scale.

$$F_O(O_b) = (f_O + \xi_b^O) \cdot O_b \sqrt{\text{Assets}_b} \tag{26}$$

The parameter f_O captures digital platform adoption costs, where O_b is an indicator variable tracking whether bank b has a digital platform, and Assets_b is bank b's assets. ξ_b^O is bank b's structural disturbance to digital platform adoption costs.

D.2. Branch Maintenance

Banks incur certain fixed branch maintenance costs as given in Equation (27). The parameter f_N captures the per-branch maintenance cost, and ξ_b^N is bank b's structural disturbance to this cost.

$$F_N(\boldsymbol{N}_b) = \sum_{c \in \mathcal{C}_b} (f_N + \xi_b^N) \cdot N_{bc} \tag{27}$$

D.3. County Entry Cost

Finally, the bank also incurs a cost when it originates loans in counties in which it does not have branches. These costs can include local market research, initiation costs, and advertising campaigns. I parameterize this cost as,

$$F_C(\mathcal{C}_b) = \sum_{c \in \mathcal{C}_b} f_C \cdot (D_{bc} + \xi_b^C) \cdot \text{Non-Local}_{bc}. \tag{28}$$

County entry costs are a function of the distance between bank b's headquarter county c_b^{HQ} and the new county c, denoted D_{bc}, where the parameter f_C captures the entry cost per unit of distance. The bank only pays entry costs for counties in which it does not already have a branch, denoted by the indicator variable Non-Local_{bc}. ξ_b^C is bank b's structural disturbance to this cost.

E. Equilibrium

An equilibrium is a banking industry structure $\{\mathcal{C}_b^*, \boldsymbol{N}_b^*, O_b^*\}_{b\in\mathcal{B}}$, loans and deposits $\mathcal{Q}_b^*$, and rates $R_b^{DI*}, R_b^{DU*}, R_{bc}^{H*}, R_{bc}^{L*}$ such that banks maximize their profits, customers maximize their utility, and markets clear. In what follows, for ease of notation, I drop the stars.

There are potentially multiple Nash equilibria due to investment decisions made at $t = 0$. In model estimation, I use the observed equilibrium to back out model parameters following the moment inequality literature (Manski, 1975, 1987, Ishii, 2004, Pakes et al., 2015, Pakes and Porter, 2016, Wollmann, 2018). In evaluation of counterfactuals, I solve for a specific Nash equilibrium under a set of further restrictions, which I describe in detail in Section VII.

VI. Model Estimation

In this section, I bring the model to the data by estimating the demand and supply parameters that appear in the banks' profit maximization, Equation (25), using cross-sectional variation and shifters of banks' demand and supply, and accounting for the endogeneity of digital platforms. This allows me to evaluate the relative importance of demand and supply side channels in explaining the reduced form facts of Section IV. In Section VI.A I estimate demand parameters, in Section VI.B I estimate supply parameters at $t = 1$, and in Section VI.C I estimate supply parameters at $t = 0$.

A. Demand Curve Parameters

As derived in Section (V), the demand that a bank b faces for a given market segment satisfies Equation (29) below for $j \in \{DI, DU\}$, the national insured and uninsured deposit markets, and Equation (30) for $j \in \{H, L\}$ and $c \in \mathcal{C}_b$, the local high and low income loan markets in county c.

$$Q_b^j = M^j \cdot s_b^j = M^j \cdot \frac{exp(\alpha_j X_b)}{1 + \sum_{b'\in\mathcal{B}} exp(\alpha_j X_{b'})} \tag{29}$$

$$Q_{bc}^j = M_c^j \cdot s_{bc}^j = M_c^j \cdot \frac{exp(\alpha_j X_{bc})}{1 + \sum_{b'\in\mathcal{B}} exp(\alpha_j X_{b'c})} \tag{30}$$

On the demand side for each market segment, I estimate the vector of demand elasticities α_j which determine banks' market shares s_b^j (and s_{bc}^j). I also estimate the market sizes M^j (and M_c^j). These two components together give the market demand curves that banks face, $\mathcal{Q}_b$.

For model estimation in loan markets I focus on mortgages due to detailed quantity and price data made available by HMDA. In contrast, data on small business loan rates are not sufficiently granular in terms of geography or market segment classifications.

A.1. Market Size

To estimate the market size for insured and uninsured deposits, I obtain the national assets held in money market mutual funds and deposits, by wealth percentile, from FRED. I decompose these holdings by income group to capture that uninsured deposits are those over $250,000 and therefore held by the top of the income distribution. I take the insured deposit market size to be the sum of deposit and money market fund holdings for households below the 90th percentile, plus 20% of the holdings among households in the top 10th percentile. For reference, in 2019 the minimum wealth cutoff for the 90th percentile was around $1.8 Million.[25] A substantial portion of uninsured deposits may belong to corporations. I effectively assume that the top of the income distribution owns these corporations as well.

To estimate the market size for high and low income mortgages, I obtain the total market size for high- and low-income mortgages from HMDA, including originations from non-bank mortgage originators. Then, I scale this overall market size by 1.2, in order to capture borrowers who do not apply for or who do not ultimately obtain a mortgage. The number 1.2 is obtained by referencing the average application denial rate during this period, which is around or slightly below 20%.[26]

A.2. Demand Estimates

In order to estimate the demand elasticities for each market segment, I take the natural logarithm of banks' demand equations and re-arrange the resulting expressions. For national insured and uninsured deposit markets $j \in \{DI, DU\}$ as given by Equation (29), I obtain the relationship in Equation (31) between log market shares and bank characteristics for bank b,

$$\log s_b^j - \log s_0^j = \alpha_j^R R_b^j + \alpha_j^N N_b + \alpha_j^{O,S} O_b S_b + \alpha_j^\Theta \Theta_b + \xi_b. \tag{31}$$

Similarly, for local high and low income mortgage markets $j \in \{H, L\}$ in counties $c \in \mathcal{C}_b$ as given by Equation (30), I obtain Equation (32) for bank b,

$$\log s_{bc}^j - \log s_{0c}^j = \alpha_j^R R_{bc}^j + \alpha_j^N N_{bc} + \alpha_j^O O_{bc} + \alpha_j^\Theta \Theta_{bc} + \xi_{bc}. \tag{32}$$

[25]Source: FRED (link).
[26]Source: NY Fed (link).

From Equations (31) and (32), the vector of demand elasticities α_j can be estimated via linear regression, where the structural errors ξ_b (and ξ_{bc}) are the residual of the regression. I estimate deposit demands in Equation (31) using bank-year panel data from 2012 to 2019. For mortgage demands in Equation (32), I use bank-county-year panel data from 2018 and 2019, during which HMDA reports rate information for mortgages. Intuitively, I estimate demand elasticities using variation on how banks' market shares vary in response to a change in a given characteristic, holding fixed all others. For instance, if banks with digital platforms, holding fixed other characteristics, have relatively higher market shares in high income mortgage markets, then α_H^O will be positive.

The last obstacle remaining in estimation of the demand elasticities is the potential endogeneity of bank characteristics. First, deposit and mortgage rates are equilibrium prices that are determined by the intersection of demand and supply. Specifically, rates may be correlated with the structural errors ξ_b (and ξ_{bc}). For example, a bank may charge a high deposit rate due to a negative demand shock by customers, captured in ξ_b. As a result, I require supply shifters of these rates in order to identify the demand elasticities and trace out the demand curve. I construct supply shifters for rates that are uncorrelated with the structural errors. For deposit markets, I follow the literature in using the expenses on fixed assets as instruments for deposit rates (see for example Xiao (2020) and Wang et al. (2020)). Specifically, I scale a banks' log expenses on operating costs by their log assets. This serves as a marginal cost shifter on operating costs and includes expenses such as lease payments, utilities, and building maintenance. For mortgage markets, I leverage the local nature of the data to construct Hausman instruments (Hausman, 1996). These instruments exploit the granular geographic variation in mortgage originations by using the average of the bank's out-of-county rates as an instrument for a bank's mortgage rate in county m, capturing the common component of the bank's marginal costs.

Further, I relax the standard assumption in the discrete choice demand estimation literature that non-price characteristics are exogenous, by allowing for the endogeneity of digital platforms. The structural errors ξ_b (and ξ_{bc}) include unobservable variation in bank characteristics and customer demand heterogeneity, and the existence of digital platforms may correlate with these unobservables. I instrument for digital platform presence again using the shift share instruments constructed in Section III based on a bank's AT&T exposure, and control for their overall coverage exposure. The assumption for identification here is that the AT&T exposure of a bank, holding fixed it's overall coverage exposure, is plausibly orthogonal to bank and customer unobservables, and shifts banks' supply of digital platforms via varying technology availability in the cross-section of banks. I winsorize banks' AT&T and overall coverage exposure annually at 1%.

With this setup, the vector of demand elasticities α_j can be consistently estimated using 2SLS, where the second stage is as in Equation (33) for each national deposit market segment $j \in \{DI, DU\}$, and Equation (34) for the local mortgage market segments $j \in \{\{L\}_c, \{H\}_c\}$.

$$\log s^j_{bt} - \log s^j_{0t} = \alpha^R_j \hat{R}^D_{bt} + \alpha^{O,S}_j \hat{O}_{bt} S_{bt} + \alpha^N_j N_{bt} + \alpha^\Theta_j \Theta_{bt} + \alpha^j_t + \xi^j_{bt} \tag{33}$$

$$\log s^j_{bct} - \log s^j_{0ct} = \alpha^R_j \hat{R}^D_{bct} + \alpha^O_j \hat{O}_{bt} + \alpha^N_j N_{bct} + \alpha^\Theta_j \Theta_{bct} + \alpha^j_t + \xi^j_{bct} \tag{34}$$

For each market, I specify a set of controls Θ_{bt} (and Θ_{bct}) that include a bank's overall coverage, and a year fixed-effect (and county-year fixed effect, respectively) to capture time series trends in demand when estimating in a panel setting. In addition, Θ_{bt} (and Θ_{bct}) includes salient characteristics that customers in this market may value: For deposit markets, Θ_{bt} additionally includes the bank's local deposit market volume size, calculated as the sum of overall deposits in markets where the bank has branches, to capture the effect of a bank's local markets on national deposit demand. I further include the bank's lagged loan loss ratio as a measure of bank risk. This captures the fact that depositors may value the safety of a bank, and that the extent to which this is the case may vary across insured and uninsured depositors. Finally, I include the lag of the bank's log assets and the lag of the bank's insured deposits ratio in order to capture baseline cross-sectional differences across banks. For loan markets, the granular nature of the data allows me to model these markets locally, and control for fewer bank characteristics: Θ_{bct} includes an indicator variable that tracks if the bank has any branches in county c, which is a key source of cross-sectional differentiation across banks for loan customers. Given that loan markets are local at the county level, I weight these regressions by the square root of the local market size winsorized at 10%, to provide representative demand elasticities for a given dollar of mortgage origination.

A.3. Demand Curve Estimation Results

Estimates for deposit demand parameters are reported in Table 9 Panel A.[27] The first row reports demand estimates for interest rates, where interest rates are measured in percentage points. For insured deposits, if a bank increases its deposit rate by 10 basis points, its market share increases by 14%. In Column (2) the rate-elasticity of uninsured depositors is higher at 23%. This is consistent with these uninsured depositors being more yield-sensitive, as observed during the banking crisis of 2023. These magnitudes fall within the ballpark of other estimates of deposit rate semi-elasticity reported in the literature.

[27] Demand parameter estimates can be interpreted as the semi-elasticity of bank market shares with respect to each characteristic for a bank with infinitesimally small market share and holding fixed all other characteristics, as derived in the Appendix.

The next three rows report demand estimates for digital platforms for banks with assets greater than \$100B, between \$10 and \$100B in assets, and below \$10B in assets. To my knowledge, these are the first estimates in the literature of these semi-elasticities. I find that if a bank with over \$100B in assets adopts a digital platform, there is no significant effect on its insured deposit market share, whereas its uninsured deposit market share increases by 67%. For mid-sized banks with between \$10B and \$100B in assets, adopting a digital platform leads to their insured deposit market share increasing by 21% while their uninsured deposit market share increases by 71%. For smaller banks with less than \$10B in assets, adopting a digital platform leads to an increase in their insured deposit market share by 17% and their uninsured deposit market share by 49%. These estimates show that mid-sized banks have the highest demand estimates for digital platforms, consistent with the countervailing forces across the bank size distribution as discussed in Sections II and IV. Further, these results also demonstrate that demand from uninsured depositors is more responsive to the release of digital platforms, providing one explanation for the increase in uninsured deposit funding following digital platform adoption as documented in Section IV, and consistent with corporations preferring digital banking. The fifth row reports the demand elasticities for the banks' number of branches. As expected, branches increase demand for both market segments. The sixth row reports the demand elasticities for banks' loan losses, a term that captures depositors' sensitivity to bank risk, and demonstrates that uninsured depositors are more sensitive to bank risk than insured depositors.

In Appendix A.6, I report two variations of these demand estimates. First, I directly model the two proposed micro mechanisms driving the inverse-U shaped response across the bank size distribution — digital platform quality and ex-ante branch network characteristics — and find that the demand response to digital platform adoption is increasing in digital platform quality and decreasing in ex-ante branch networks that are larger and of lower quality. I additionally report a simple demand specification without interacting digital platforms with bank size categories. In each case, I find that the baseline semi-elasticity of bank market shares to adopting digital platforms in the insured deposit market ranges between 20-21%. This estimate is useful not only to understand the effects of digital platform adoption by traditional banks, but also digitalization in other areas of the banking sector such as the introduction of CBDC, as used in Whited et al. (2022a).

Estimates for loan demand parameters are reported in Table 10 Panel A. The first row reports demand estimates for interest rates, where interest rates are measured in percentage points. For the high income mortgage market, I find that if a bank increases its mortgage rate by 10 basis points, it loses 6.6% market share. For the low income mortgage market, this number is 5.6%.

The second row reports demand estimates for digital platforms. For high income mortgages, I find in Column (1) that a bank increases its market share in a county c by a factor of 2.27 if it adopts digital platforms. For reference, the fourth row reports that having at least one branch in the local market increases a bank's market share by a similar amount. In sharp contrast, in Column (2) I find that there is no significant increase in market share for low income mortgage markets in response to a bank offering a digital platform. This lack of response is consistent with the reduced ratio of low income mortgage originations by banks that adopt digital platforms, and the reduced ratio of low income loan applications that they receive, as documented in Section IV, and suggests that these customers do not prefer to or are less able to apply for mortgages digitally. The third row reports the demand elasticities for the banks' number of branches. As expected, branches increase demand for both high and low income mortgages.

B. Supply Parameters at $t = 1$

B.1. Expected Loan Losses

Banks' expected loan losses satisfy Equation (22). In this section I estimate the loan loss parameters, i.e. p_b and the δ's that appear in (22), using bank-level panel data from 2010 through 2019. For ease of interpretation, I divide both sides of the equation by the total quantity of loans that bank b has on its balance sheet, Q_{bt}^{Bal}, in order to obtain on the left hand side the per-unit loss. I map this empirically to banks' loan loss allocations divided by banks' balance sheet quantity of loans, as reported in their regulatory Call Reports. I restrict to banks whose mortgage originations in a given year represent greater than 2% of their loan portfolio. Specifically, I estimate,

$$
\begin{aligned}
\text{Per Unit Loss}_{b,t} = & \underbrace{\delta^O O_{bt} \frac{(Q_{bct}^L + Q_{bct}^H)}{Q_{bt}^{Bal}} + \delta_L^O O_{bt} \frac{Q_{bt}^L}{Q_{bt}^{Bal}} + \delta_H^O O_{bt} \frac{Q_{bt}^H}{Q_{bt}^{Bal}}}_{\text{Effect of Digital Platforms}} \\
& \underbrace{+\delta^N \frac{\sum_{c \in \mathcal{C}} N_{bc}(Q_{bct}^L + Q_{bct}^H)}{Q_{bt}^{Bal}} + \delta_L^N \frac{\sum_{c \in \mathcal{C}} N_{bc} Q_{bct}^L}{Q_{bt}^{Bal}} + \delta_H^N \frac{\sum_{c \in \mathcal{C}} N_{bc} Q_{bct}^H}{Q_{bt}^{Bal}}}_{\text{Effect of Branches}} \\
& \underbrace{+\delta_U \text{Per Unit Loss}_{b,t-1} + \delta_C \text{Coverage}_b + \delta_t + \xi_{bt}}_{\text{Baseline Per-Unit Loss}}.
\end{aligned}
\tag{35}
$$

As discussed in Section V, a bank b's per-unit losses in Equation (35) depend on several factors. Beginning from the bottom of the expression, first there is a baseline per-unit loss, which is determined by a bank-specific monitoring ability. I account for this monitoring ability through the inclusion of several controls: δ_U captures cross sectional variation in bank losses that are unrelated to new originations as well as the general riskiness of bank b's loan origination behavior, δ_C is a coefficient on banks' overall coverage exposure, δ_t is a year fixed effect to absorb time variation in lending opportunities and associated risks, and ξ_{bt} is structural disturbance to bank b's baseline screening ability in year t.

Second, the first two terms in Equation (35) capture the effect that investments in information technologies — branches and digital platforms — have on this baseline per-unit loss. Notice that these effects may depend on the shares of lending to borrowers of low and high income.

Intuitively, I estimate loan loss parameters using variation on how banks' per-unit loan losses vary in response to the existence of digital platforms and branches, as well as their composition of lending across high and low income mortgages. For instance, when holding all other terms constant, if banks with digital platforms tend to have lower per-unit loan losses, then $\delta^O < 0$. Further, if banks with digital platforms that do more high income mortgage lending have even lower per-unit loan losses relative to banks that have digital platforms but do less high income mortgage lending, then $\delta^O_H < 0$. I account for the endogeneity of digital platform presence by instrumenting for digital platforms with banks' AT&T exposure and controlling for banks' overall coverage exposure. The identification assumption here is that AT&T coverage shifts banks' digital platform presence in a way that is orthogonal both to unobservable monitoring or screening ability as well as loan customer riskiness.

Expected loan loss estimates are reported in Table 10 Panel C. For branches, δ_N is negative, which is consistent with monitoring or screening facilitated via branches reducing expected loan losses for both high and low income mortgages. For digital platforms, the level effect δ_O enters insignificantly. However, the interaction term of digital platforms with high income mortgages, δ^H_O is negative, so that digital platforms help to reduce expected loan losses for high income mortgages. In sharp contrast, the coefficient on the interaction with low income mortgages, δ^L_O is positive, implying that digital platforms erode banks' ability to monitor these more relationship-intensive loans and lead to higher expected losses for this market segment.

For example, the following are two possible mechanisms that may explain this result. First, the presence of digital platforms may make borrowers less likely to visit branches, which lowers in turn the amount of intangible information that banks have about these borrowers. This information may be particularly important for low income borrowers. Indeed, the proportion of households that report branches as their main method of accessing banking services has fallen from 32% in 2013 to below 15% in 2021.[28] Second, banks may reduce

[28]Source: FDIC National Surveys of Unbanked and Underbanked Households (link).

investments in the quality of their branch loan officers after adopting digital platforms in order to focus more resources on digital service provision. Industry reports and interviews with bank executives point to a significant culling of branch workforces as banks transition to digital service provision.[29]

B.2. Service Provision Costs

To estimate the parameters that appear in banks' service provision costs, I take the first order conditions associated with bank b's profit function, Equation (20), which once rearranged yields,

$$FOC_{R^j}: \quad \underbrace{f - R^j - Q^j \left(\frac{\partial Q^j}{\partial R^j} \right)^{-1}}_{Spread_b^j} = \frac{\partial \Phi_b^j}{\partial Q^j} \quad \text{for } j \in \{DI, DU\} \tag{36}$$

$$FOC_{R_c^j}: \quad \underbrace{R_c^j - f + Q_c^j \left(\frac{\partial Q_c^j}{\partial R_c^j} \right)^{-1} - \frac{\partial L}{\partial Q_c^j}}_{Spread_{b,c}^j} = \frac{\partial \Phi_{bc}^j}{\partial Q_c^j} \quad \text{for } j \in \{H, L\}\ ,\ c \in C_b. \tag{37}$$

The left-hand sides of Equation (36) and (37) are observed in the data after demand parameters are estimated. In other words, if banks are maximizing profits subject to the estimated demand curves and loan losses, then the loan spread that they choose in equilibrium, above and beyond their markup and their loan losses in the case of mortgage markets, reveal what their marginal costs are. I parameterize marginal service costs as in Equations (23) and (24), which I now combine with banks' first order conditions to arrive at the following expressions.

$$\text{Spread}_b^j = \phi_j^N N_{bc} Q_b^j + \phi_j^{Q,S} Q_b^j S_b + \phi_j^{O,S} O_b Q_b^j S_b + \phi_j^\Theta \Theta_b + \xi_b^j \quad \text{for } j \in \{DI, DU\}$$
$$\text{Spread}_{b,c}^j = \phi_j^N N_{bc} + \phi_j^O O_b + \phi_j^\Theta \Theta_{bc} + \xi_{bc}^j \quad \text{for } j \in \{H, L\}\ ,\ c \in C_b$$

I estimate these expressions using panel data from 2010 through 2019 for deposits, and 2018 through 2019 for loans. In the vector of controls Θ_b (and Θ_{bc}) I include a year fixed effect to capture variation in costs by year. The inclusion of a year fixed effect means that estimates are based only on cross-sectional variation in marginal costs. For loan markets $j \in \{H, L\}$ I additionally include the median income of households in the county in order to capture cross-sectional cost differences.

[29] For instance, FirstBank CEO Jim Reuter states that "Even though traditional teller positions and paperwork-heavy jobs in loan processing have declined, banks have hired new armies of technologists, cybersecurity experts, developers and data analysts" (link).

Intuitively, I estimate service cost parameters using variation on how banks' deposit and mortgage spreads vary in response to the existence of digital platforms and branches. For instance, when holding all other terms constant, if banks tend to charge lower spreads for high income mortgages when they have a digital platform, then $\phi_H^O < 0$.

Finally, I account for potential endogeneity. Variation in deposit quantities can be due not only to changes in demand, but also variation in bank supply. In order to estimate the marginal service provision cost parameters above, I need shifters of quantities Q_b^j for $j \in \mathcal{J}$ that are independent of the unobservable supply disturbances ξ_b^j. I use bank b's local population as a demand shifter. This is calculated as the sum of the population of all counties where bank b has branches. The intuition is that banks which are located in areas that have a larger market will face a relatively higher demand for their products.

The presence of digital platforms O_b is also an endogenous choice variable. To account for this, I estimate the marginal cost parameters by shifting demand for digital platforms using the demographics of customers present in banks' markets as instruments. For deposit markets, I use the average income of customers present in the counties that the bank operates branches in, weighted by the banks' number of branches in each county. As documented in Section IV, digital banking particularly facilitates provision of services to higher income customers, so that banks near wealthier populations likely face higher demand for digital services. For loan markets, I use instead the average proportion of the population over 60, since these loan markets are defined using income of borrowers. Jiang et al. (2022) show that older banking customers have a lower preference for digital services, so that banks near older populations are likely to face a lower demand for digital platforms.

Service cost estimates for deposits are reported in Table 9 Panel B. The first three rows reports the baseline cost parameters for banks with above \$100B in assets, between \$10B and \$100B in assets, and below \$10B in assets. For insured deposits, I find significant differences across these baseline parameters by bank size category. Insured deposits entail marginal costs that are increasing in quantities, and the magnitude of this increase tends to be lower for larger banks, consistent with the discussion in Section II that large banks tend to have a more efficient baseline business model. The following three rows report the effect of digital platforms on these baseline costs. I find that digital platforms reduce the marginal costs of providing insured deposits by more for smaller banks. In contrast, for uninsured deposits I find that marginal costs do not vary significantly with quantities, branches, or digital platforms, reflecting that managing the deposits of high net worth clients or corporations appears to entail a different cost structure than that of smaller retail deposits. Thus, while the demand estimates suggest that uninsured depositors prefer banks with digital platforms, these platforms do not lead to cost savings for banks in serving this market segment.

Service cost estimates for loans are reported in Table 10 Panel B. The first row reports the effect of digital platforms on marginal costs. I find that digital platforms reduce the costs of originating mortgages to both high and low income borrowers. The second row reports the effect of branches on marginal costs, which also decreases the costs of providing mortgages in both market segments.

Taken together, the service cost estimates show that first, larger banks operate with lower baseline variable costs. Second, branches and digital platforms both reduce the variable costs of providing services. Third, digital platforms have less of an effect on the variable costs of large banks, reflecting their ex-ante more efficient business models even in the absence of digital platform technology.

C. Supply Parameters at $t = 0$

At $t = 0$, banks make investment decisions regarding digital platform adoption, branch networks, and county entry decisions, to maximize their profits, as in Equation (25). The last challenge, thus, is the estimation of the cost parameters associated with these investment decisions in (25). These costs are estimated through revealed preference of banks according to the moment inequality literature (Manski, 1975, 1987, Ishii, 2004, Pakes et al., 2015, Pakes and Porter, 2016). I relegate the technical details and assumptions of this moment inequality estimation to the Appendix. The basic estimation methodology is as follows.

I begin by assuming that banks are profit maximizing in the observed equilibrium. In that case, via revealed preferences, the expected returns from the strategy played should be at least as large as the expected returns from the strategies that were not played. Based on this intuition, I construct profit inequalities arising from deviations to banks' observed best responses. The deviation I consider depends on specific fixed cost I aim to uncover. For digital platform adoption, I compare adopting versus not adopting. For branching decisions, I consider deviations based on opening or closing a branch. For county entry decisions, I consider deviations based on entering or not entering a county. In each case, I solve for banks' optimal rates in the subsequent period at $t = 1$ given their investment deviation at $t = 0$. These deviations give rise to upper and lower bounds for the fixed cost parameters.

Finally, a potential endogeneity concern is that there may be unobservable cost differences across banks that correlate with their investment decisions. Below, I address this concern for each parameter of interest.

Fixed cost estimates are reported in Table 11, and discussed in detail below. For each cost, I report the lower and upper bound in parentheses, and the mid-point of the interval as the estimate.

C.1. Adoption Cost

I obtain a lower bound for f_O by considering the change in $t = 1$ profits if banks that do not adopt in equilibrium were to adopt digital platforms, as in Equation (38) below. I obtain an upper bound for f_O by considering the change in $t = 1$ profits if banks that do adopt in equilibrium were to not adopt (Equation (39)). The intuition is that the overall fixed cost F_O (see Equation (26)) must be larger than the $t = 1$ change in profit for non-adopters, and smaller than the $t = 1$ change in profit for adopters. I follow Pakes et al. (2015), Wollmann (2018), and Bontemps et al. (2021) in applying a generalized instrumental variables approach to this inequality setting, to account for the fact that the adoption costs for adopters are likely to be unobservably low, and vice-versa for non-adopters. I construct the instruments Z^+, Z^- again using variation in banks' AT&T presence, where Z^+ is equal to 1 if a bank's AT&T presence is above the 50th percentile, and 0 otherwise. Z^- is equal to 1 when Z^+ is equal to 0. The identification assumption is that a banks' AT&T exposure is orthogonal to their unobservable cost disturbance.

$$\frac{1}{B}\sum_b [Z_b^-(\Delta\hat{\pi}(1, d_{-b}, r_b) - \Delta\hat{\pi}(0, d_{-b}, r_b)) \cdot \text{Assets}_b^{-1/2} | O_b^* = 0] \leq f_O \tag{38}$$

$$\frac{1}{B}\sum_b [Z_b^+(\Delta\hat{\pi}(1, d_{-b}, r_b) - \Delta\hat{\pi}(0, d_{-b}, r_b)) \cdot \text{Assets}_b^{-1/2} | O_b^* = 1] \geq f_O \tag{39}$$

Here, the structural error ξ_b^O has dropped out due to multiplying the inequalities by the instrumental variables Z^+, Z^-. I use the lag of bank assets to capture assets at the beginning of the period, measured in \$100 millions.

In the first column of Table 11, I find the digital platform adoption cost parameter f_O to range between 398,800 and 416,600, with a mid-point of 407,700. To give a sense of the overall magnitude of these costs, I apply Equation (26) to a bank with \$100B in assets. In this case, the overall cost of platform adoption, F_O would be roughly \$12.6M. Instead, for a bank with \$10B in assets, F_O would be \$4M. These costs entail not only the direct costs of developing and launching the platform, but also the re-organization costs of adjusting to a business with a digital front-end, which can be significant.

C.2. Branch Maintenance Cost

I obtain a lower bound for f_N from the deviation of opening a new random branch as in Equation (40) below. I obtain an upper bound for f_N from the deviation of closing a random branch in Equation (41). Intuitively, it must be that the overall fixed cost F_N (see Equation (27)) is larger than the $t = 1$ benefit of opening a new branch, thus Equation (40) provides a lower bound for v, and the fixed cost must be smaller than the $t = 1$ benefit of keeping open a branch observed to exist in equilibrium, so that Equation (41) provides an upper bound for f_N.

$$\frac{1}{B}\sum_b [\hat{\pi}(d+1, d_{-b}, r_b) - \hat{\pi}(d, d_{-b}, r_b)] \leq f_N \tag{40}$$

$$\frac{1}{B}\sum_b [\hat{\pi}(d, d_{-b}, r_b) - \hat{\pi}(d-1, d_{-b}, r_b)] \geq f_N \tag{41}$$

Here, $\hat{\pi}(d+1, d_{-b}, r_b)$ is bank b's $t = 1$ profit from opening a new branch $d+1$, holding fixed the actions of other banks d_{-b}, and solving for bank b's new optimal rates at $t = 1$, r_b. Similarly, $\hat{\pi}(d, d_{-b}, r_b)$ is bank b's $t = 1$ profit from d branches, holding fixed the actions of other banks d_{-b}, and solving for bank b's optimal rates at $t = 1$, r_b.

In these moment conditions, the structural error ξ_b^N has been differenced out due to the ordered nature of the branching decision, as detailed in Ishii (2004) and Pakes et al. (2015). See Appendix A.4 for more details.

In the second column of Table 11, I the find per-branch maintenance cost parameter f_N to have a lower bound of \$25,270 and an upper bound of \$26,010, with a midpoint of \$25,640 is my parameter value for f_N.[30]

C.3. Market Entry Cost

I obtain a lower bound for f_C by considering a deviation of entering a new random county as in Equation (42) below, and an upper bound for f_C by considering a deviation of exiting a random county in Equation (43). Intuitively, it must be that the overall fixed cost F_C (see Equation (28)) is larger than the $t = 1$ benefit of entering a county that bank b does not enter in equilibrium, and similarly the fixed cost must be smaller than the $t = 1$ benefit of being in a county that bank b is present in in equilibrium.

$$\frac{1}{B}\sum_b \frac{[\hat{\pi}(d_+, d_{-b}, r_b) - \hat{\pi}(d, d_{-b}, r_b)]}{D_{bc'}} \leq f_C \tag{42}$$

$$\frac{1}{B}\sum_b \frac{[\hat{\pi}(d, d_{-b}, r_b) - \hat{\pi}(d_-, d_{-b}, r_b)]}{D_{bc'}} \geq f_C \tag{43}$$

In these moment conditions, the structural error ξ_b^C has dropped out due to the assumption that conditional on the distance of the market to bank b's headquarters, $D_{bc'}$, ξ_b^C is mean independent of bank b's decision to be present in that county.

[30]This cost may appear low in dollar terms, which may be due to the parsimonious parameterization of branches throughout the model. Current research is geared towards relaxing this.

In the third column of Table 11, I find county entry costs f_C per mile of distance between the new market and the headquarters of a bank to range between \$10.80 and \$318.00, with a midpoint of \$164.40. This translates to a bank incurring an entry cost of around \$16,440 in order to enter a county that is 100 miles away.

VII. How Has Digital Banking Altered Competition and Stability?

Armed with the model estimates, I next turn to assessing the aggregate effects of digital banking, and quantifying the financial stability implications, which are the central questions of my paper.

To assess the current effects of digital banking on aggregate outcomes, I compare the observed equilibrium with a counterfactual equilibrium in which digital platform technologies are not available. Without the development of digital platforms, banks may not have closed as many branches, or branchlessly entered as many counties to provide banking services. Further, non-bank mortgage providers would also not have access to digital platform technologies. Accordingly, when calculating the counterfactual equilibrium I allow banks to adjust their branches, exit markets, and I adjust the utility of the outside option. I refer to the observed equilibrium as the "digital equilibrium", and the counterfactual equilibrium as the "non-digital equilibrium". Details on the equilibrium computation are reported in Appendix A.4.C.

To examine the effect on the competitive landscape of the banking sector, I evaluate changes in market concentration, integration, markups, consumer surplus, and bank profits. I find that market concentration decreases, local banking markets become branchlessly more integrated, and that the value-weighted markup that customers face in deposit and loan markets, holding fixed the share of the outside option, falls. Lower markups are indicative of increased competition as prices approach marginal costs. Further, consumer surplus increases proportionally more than bank profits, suggesting that customers are able to capture more of the overall surplus in the digital equilibrium. However, increases in consumer welfare accrue mostly to wealthier segments of the economy: uninsured depositors and high income mortgage borrowers. Next, I examine implications for financial stability. I find that mid sized banks grow larger and expand geographically, so that their failure would lead to a larger and more geographically widespread effect on the financial system. Additionally, I find that the uninsured deposit ratio in the banking sector increases and that there is a resorting of uninsured deposits towards digital banks. Finally, I find that credit risks may build up in market segments that are less well served by digital technologies

A. Competition

I quantify how digital banking platforms affect competition. First, I evaluate several measures of market concentration. In the first row of Table 12 Panel A, I look at the Herfindahl-Hirschman Index (HHI) of the banking sector, defined below,

$$\text{HHI} = \sum_{b \in \mathcal{B}} \text{Market Share}_b^2,$$

and where an HHI close to 0 suggests low market concentration while an HHI close to 1 implies the existence of a monopoly. I calculate the HHI of the banking sector using banks' market shares in the national deposit market, summing across their insured and uninsured deposits. I find that the HHI of the banking sector decreases by 6.9% as a result of digital platforms. In the second row, I consider an alternate measure of market concentration, the *Top Share*, which is the aggregate share of deposit services provided by banks with assets above $100B, and find that this share has also decreased, falling by 1.7%. Both of these measures are consistent with digital platforms reducing market concentration.

Second, I examine market integration. In the third row of Table 12, I consider the average number of banks that are present in a county, and find that this has increased by 8.2%. In the fourth row, I look at the average banks' number of branches, and find that this has decreased by 5.8%. Together, this evidence suggests that digital platforms have *branchlessly* increased market integration.

Third, I turn to markups, quantities, and expected consumer surplus for deposit and mortgage markets in Table 12 Panel B. I calculate the change in volume-weighted markups while excluding the outside option market share, which I call the "adjusted markup". This adjustment captures changes in market power within the banking sector, while remaining neutral on the relative desirability of banks versus the outside option. In deposit markets, I find that this adjusted markup has fallen by 0.3%, consistent with an increase in competition. In mortgage markets, I report the average change in adjusted markup across counties, and find that it has decreased by 7.7%, again consistent with an increase in competition.

Banks' deposits increase in aggregate by 6.3%. As for mortgages, banks' originations increase in aggregate by 60.3%. During my sample period, digitalization has also affected mortgage underwriting by non-banks. In my framework, this is taken into account by allowing the non-banks in the outside option to also have digital platforms in the digital equilibrium. Thus, this growth in banks' mortgages is the effect solely attributable to banks' digitalization.

Expected consumer surplus under the Logit model is equal to,

$$E[CS] = \frac{1}{\alpha}\log\left(\sum_{j=0}^{J}\exp(\alpha_j X_b)\right),$$

where α is the marginal utility of income. In my framework, the marginal utility of income is either the demand elasticity for deposit rates, or the negative demand elasticity for mortgage rates, for which we already have estimates. Details on consumer surplus derivation and calculations for each market segment are reported in Appendix A.4.C. Expected consumer surplus increases for both deposit and mortgage markets. In deposit markets expected consumer surplus increases by 15.1%, while for mortgage markets it increases by 239.6%, reflecting the high value that mortgage customers place on the availability of digital services. I further find that the effects vary across market segments. The change in consumer surplus accrues overwhelmingly to high income borrowers and uninsured depositors. This evidence suggests that this technological change disproportionately favors wealthier segments of the economy.

Finally, in Table 12 Panel C I turn to bank profits. I scale banks' percentage change in profits from loan origination by the share of assets that these originations represent to capture how these changes affect banks' overall change in profitability. The implicit assumption is that the share and profitability of other assets in banks' balance sheets is unaffected by digitalization. First, I find that banks' aggregate profits remain unchanged. Comparing this with Panel B, the expected consumer surplus increases proportionally more than aggregate bank profits in the digital equilibrium. Digital banking technology creates additional surplus, and these results suggest that customers are able to capture more of the total surplus created in the digital equilibrium. Second, this masks large heterogeneity across the bank size distribution: the profits of large and mid-sized banks increase while those of small banks with under \$10B in assets fall, consistent with digital platforms increasing the economies of scale in banking.

B. Financial Stability

With these digital and non-digital equilibria I next evaluate the risks to financial stability along several dimensions.[31] I use the term "more systemic" to refer to an increase in banks' asset size along with an increase in the geographic presence of their service provision: a shock, for example, to the bank's capital will have a larger effect on the aggregate and in

[31] Changes in competition may also have indirect effects on financial stability through altering the risk-taking behavior of banks (See Boyd and De Nicolo (2005), Beck et al. (2006), Berger et al. (2009), Martinez-Miera and Repullo (2010), Anginer et al. (2014), and Jiang et al. (2018)).

more markets.[32] As a result of the flattening of the bank size distribution, medium-sized banks become more systemic while larger banks' influence is attenuated. To quantify the change in mid-sized banks' systemic importance, in Table 13 Panel A I consider the change in average market share across market segments for banks across the size distribution, as well as the change in the number of local banking markets that these banks are present in. I find that mid-sized banks with assets between \$10B and \$100B on average provide 29.0% more services and serve 6.9% more markets.

Second, in Table 13 Panel B I consider implications for banks' credit risks, as measured by changes to their expected loan losses. First I calculate how bank-level and aggregate average per-unit expected loan losses change as a result of digital platform technologies. At the bank-level, the average bank's expected losses per dollar of loan decrease by 35.2% and at the aggregate level, the banking sector's average expected losses per dollar of loan decreases by 37.9%.

Next, I look separately at expected loan losses for lending in low and high income market segments. In order to do so, I consider the component of banks' expected loan losses in my model that relate to a specific market segment. For instance, for loan losses related to low-income mortgage lending, I include bank-specific monitoring or screening ability, and terms related to all lending or low income lending; I exclude terms related specifically to high income lending. The resulting equation is,

$$\begin{aligned}\text{Per Unit Loss}^L_{b,t} = (\delta^O + \delta^O_L)\frac{O_{b,t}Q^L_{bt}}{Q^{Bal}_{bt}} + (\delta^B + \delta^B_L)\frac{\sum_c B_{bc}Q^L_{bct}}{Q^{Bal}_{bt}} \\ + \delta_U \text{Per Unit Loss}_{b,t-1} + \delta_C \text{Coverage}_b + \delta_t + \xi_{bt}.\end{aligned} \tag{44}$$

I find that in aggregate, the per-unit loan losses associated with lending to high income borrowers decrease by 48.4%, but those associated with lending to low income borrowers increase by 119.2%. This result suggest that the digitalization of banking may lead to a build up of credit risks within segments of the banking system that are less well served by digital technologies.

Third, in Table 13 Panel C I consider implications for banks' funding risk. I find that the aggregate uninsured deposits ratio of the banking sector increases by 8.5%, and further that that there is a re-sorting of uninsured deposits towards larger banks with digital platforms within the banking sector. Digital banks with over \$100B in assets increase their uninsured

[32] I do not take a stance on the effect that this growth and geographic expansion will have on banks' probability of default. There is a large literature examining measures of banks' systemic risk in greater detail which also take default probability into account (Acharya et al., 2017, Adrian and Brunnermeier, 2011, Brownlees and Engle, 2017).

deposit ratio by 17.6%, whereas digital banks with between $10B and $100B in assets increase their uninsured deposit ratio by 7.7%. Uninsured depositors have a higher sensitivity to both interest rates as well as bank risk, as can be seen from the results of the deposit demand estimation in Section VI. As a result, both the banking sector as a whole and digital banks in particular have a flightier deposit base in the digital equilibrium.

VIII. Conclusion

This paper documents that digital platforms increase competition in the banking sector and pose risks to financial stability. Understanding the implications of this new technological landscape in banking will remain important looking to the future as digital banking becomes more ubiquitous, in part spurred by the Covid-19 pandemic.[33] Moreover, the findings in this paper relate more broadly to understanding how technology is altering society, and highlight several trends that are of interest to policymakers.

First, the effect of digital platforms on bank competition relates to a literature studying how information technologies are leading to "second industrial revolution" in service industries (Begenau et al., 2018, Autor et al., 2020, Ayyagari et al., 2020, Hsieh and Rossi-Hansberg, 2023). This literature highlights that developments in back end IT can lead to the rise of "star firms", resulting in increased local competition as these firms expand geographically, but reducing national competition as these same firms gain more of the national marketshare. I show instead that front end IT such as digital platforms have the scope to increase competition by allowing mid-sized firms to compete more effectively with the physical infrastructure of the largest firms. Despite the potential for digital platform technologies to facilitate growth among mid-sized banks, regulators should be aware that the costs of digitalization and differences in the ability of smaller banks to keep up with technological innovations can hurt the profitability and business models of small community banks with below $10B in assets. While digital banking may increase the barriers of entry for small community banks, recent years have seen the emergence of digital-only entrants. The effects on and implications of both traditional community banks and these new digital entrants warrants further research.

Second, the digitalization of banking has implications for monetary policy transmission. I show that digital banks attract a different and potentially flightier deposit base. The 2023 banking crisis highlights the dangers of a deposit base that is mostly comprised of uninsured deposits (Jiang et al., 2023). Further, I show that digital banking also reduces the variable costs of deposit provision. Variable costs tending towards zero has implications on the value

[33] Financial Times, *Covid Nudges US Bank Customers into Digital Era* (link).

of the deposit franchise, as well as how the value of the deposit franchise varies in response to changes in market interest rates (Drechsler et al., 2020, 2023). In a related analysis Koont et al. (2023) show that digital banks also face higher deposit outflows for each deposit market segment in response to increases in interest rates, leading to a lower deposit franchise value for a given level and composition of deposits.

Third, I show that digital banking alters banks' ability to screen or monitor customers across different market segments, and may lead to a build up of risks in market segments that are less well served via digital technologies. The erosion of banks' monitoring ability for more relationship-focused market segments also has implications for the continued "specialness" of banks relative to capital markets (Ashcraft, 2005), affecting credit provision to these segments of the economy, and potentially leading to more cyclical lending (Bolton et al., 2016, Cortés and Strahan, 2017). Further, a shift towards digital loan origination increases the banking system's reliance on hard information, such as credit scores, and thus mistakes or mechanical changes in these metrics can lead to larger consequences (Bolton et al., 2012, Piskorski et al., 2015, Mian and Sufi, 2017, Dobbie et al., 2020, Purnanandam and Wirth, 2023). Finally, the increased use of hard information in lending decisions could alter the correlation among banks' risks if for instance all banks are using the same data in credit decisions, which would have implications for stability (Goldstein et al., 2022), and is an important area of future research.

Fourth, the branchless integration of local banking markets due to digital platform technologies is likely to affect the propagation of bank health shocks to more geographic regions, while also dampening the reliance of regions on any one specific institution (Bord et al., 2015). The branchless nature of this expansion highlights that branch-based measures of market concentration will become less relevant going forward in assessing the competitive landscape of a local banking market, and highlights the need for clearer data on the locations of deposits and other banking services that need not be tied to the physical branches of banks.

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Tables

A. Reduced Form Results

Table 1 Instrument First Stage

	Digital		
	(1)	(2)	(3)
ATT Coverage	0.57***	0.57***	0.43***
	(0.11)	(0.11)	(0.11)
Overall Coverage	-0.00**	-0.00**	-0.00***
	(0.00)	(0.00)	(0.00)
Nonbank Fintech Exposure		0.08	0.15
		(0.15)	(0.15)
Prop Over 60			-0.49***
			(0.14)
Median Income			-0.03
			(0.02)
Prop Urban			0.11***
			(0.02)
Year FE	Yes	Yes	Yes
Observations	50358	50358	50358
Adjusted R^2	0.264	0.264	0.271
F	23.15	15.50	24.36

This table reports the slope estimates from the first stage of a 2SLS regression, where banks' digital platform adoption is instrumented via banks' AT&T exposure. The sample period is from 2010 to 2019. Observations are at the bank-year level, and the specification includes controls for banks' overall cellular exposure and a year fixed effect. Standard errors are clustered at the bank level and reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2 Bank Geographic Expansion

	All		High Inc		Low Inc	
	(1)	(2)	(3)	(4)	(5)	(6)
Digital	0.99**	0.86**	1.33**	1.24**	0.70**	0.53*
	(0.42)	(0.37)	(0.56)	(0.52)	(0.32)	(0.28)
Overall Coverage	0.00**	0.00**	0.00**	0.00**	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L.Y	0.70***	0.71***	0.65***	0.66***	0.74***	0.76***
	(0.03)	(0.03)	(0.05)	(0.05)	(0.02)	(0.02)
L.Br Num Markets	0.01**	0.02***	0.01*	0.01*	0.02***	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Nonbank Fintech Exposure	-0.42	-0.37	-0.36	-0.34	-0.50**	-0.43*
	(0.31)	(0.29)	(0.38)	(0.38)	(0.25)	(0.23)
Log Change Establishments		-0.19**		-0.21		-0.11
		(0.10)		(0.13)		(0.11)
Log Change Employment		0.11		0.20		-0.05
		(0.11)		(0.13)		(0.13)
Log Change Payroll		0.07		-0.01		0.18**
		(0.07)		(0.09)		(0.09)
Log Change Dep Growth		0.02		0.02		-0.02
		(0.02)		(0.03)		(0.03)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23543	21644	23543	21644	21953	20177
F	27.53	27.28	24.78	24.46	30.38	30.23

This table reports the slope estimates from the second stage of a 2SLS regression of measures of bank geographic expansion of service provision on digital platform adoption, instrumented via banks' AT&T exposure. Column (1) considers the log number of markets in which banks originate mortgages, column (2) the log number of markets in which banks originate mortgages to borrowers above median income, and column (3) to borrowers below median income. All specifications include controls for the lagged dependent variable, the banks' overall cellular exposure, banks' lagged number of markets with branches, and include a year fixed effect. Observations are at the bank-year level. The sample period is from 2010 to 2019. Standard errors are clustered at the bank level and reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3 Bank Branch Response

	(1) Num Markets	(2) Num Markets	(3) Within-Market
Digital	-0.007	-0.008	-0.059*
	(0.024)	(0.024)	(0.032)
L.Num Markets	0.997***	0.997***	0.004
	(0.004)	(0.004)	(0.003)
L.Within-Market			0.983***
			(0.001)
Nonbank Fintech Exposure		-0.019	
		(0.023)	
Overall Coverage	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)
FE	Year	Year	County-Year
Observations	50,357	50,357	212,798
F	177.45	179.20	325.71

This table reports the slope estimates from the second stage of a 2SLS regression on measures of banks' branching response on digital platform adoption, instrumented via banks' AT&T exposure. Column (1) considers the log number of new markets that banks enter by opening a branch, and column (2) considers the log number of branches that banks have within-market. Column (1) is at the bank-year level from 2010 to 2019, and includes controls for the lagged dependent variable, banks' overall cellular exposure, and includes a year fixed effect. Column (2) is at the bank-county-year level from 2010 to 2019, and includes controls for the lagged dependent variable, the banks' out-of-county overall cellular exposure, the lagged log number of markets with branches, and includes a county-year fixed effect. Standard errors are clustered at the bank level and reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4 Bank Balance Sheet Growth

	Assets			Deposits			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Digital, \$100B+	-0.001	-0.002	-0.010	0.007	0.006	-0.001	0.000
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.006)
Digital, \$10B – \$100B	0.038***	0.036***	0.034***	0.042***	0.040***	0.038***	0.025***
	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.010)	(0.008)
Digital, \$10B–	-0.012	-0.015	-0.009	-0.012	-0.015	-0.009	-0.018
	(0.015)	(0.015)	(0.013)	(0.017)	(0.017)	(0.014)	(0.013)
Overall Coverage	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.Y	0.464***	0.465***	0.458***	0.415***	0.416***	0.419***	0.587***
	(0.012)	(0.012)	(0.014)	(0.012)	(0.012)	(0.015)	(0.011)
Nonbank Fintech Exposure		-0.068***	-0.070***		-0.071***	-0.072***	-0.050***
		(0.016)	(0.015)		(0.017)	(0.017)	(0.013)
Est. Growth			0.031***			0.033***	
			(0.010)			(0.011)	
Emp. Growth			-0.013***			-0.013***	
			(0.003)			(0.003)	
Payroll Growth			0.010**			0.010**	
			(0.004)			(0.005)	
Deposit Growth			0.057***			0.064***	
			(0.008)			(0.009)	
Bank Loan Growth							0.436***
							(0.015)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49463	49463	43894	49373	49373	43813	49340
F	48.35	48.81	49.22	47.87	48.25	48.90	48.27

This table reports the slope estimates from the second stage of 2SLS regressions of measures of bank balance sheet growth on digital platform adoption, instrumented via banks' AT&T exposure, and interacts digital platform adoption with indicator variables for bank size categories. Columns (1) through (3) consider balanced asset growth, and columns (4) through (7) consider balanced deposit growth. All specifications include controls for the lagged dependent variable, the banks' overall coverage exposure, the lagged number of markets with branches, and include a year fixed effect. Columns (2) and (5) additionally control for nonbank fintech exposure of the bank. Columns (3) and (6) additionally control for the centered growth rate for four measures of local economic and business growth (described in Section III). Finally, column (7) controls for the change in the banks' centered loan growth rate. Observations are at the bank-year level from 2010 to 2019. Standard errors are clustered at the bank level and reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5 Bank Insured Deposit Ratio

	Insured Deposit Ratio		
	(1)	(2)	(3)
Digital, \$100B+	-0.017**	-0.017**	-0.012
	(0.009)	(0.009)	(0.008)
Digital, \$10B – \$100B	-0.024***	-0.023***	-0.016**
	(0.009)	(0.009)	(0.008)
Digital, \$10B–	0.006	0.007	0.006
	(0.008)	(0.008)	(0.007)
Overall Coverage	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
L.Insured Deposit Ratio	0.945***	0.945***	0.971***
	(0.011)	(0.011)	(0.008)
Nonbank Fintech Exposure		0.018**	0.016*
		(0.009)	(0.009)
Log Change Establishments			0.002
			(0.005)
Log Change Employment			0.004
			(0.003)
Log Change Payroll			-0.004
			(0.003)
Log Change Dep Growth			-0.011***
			(0.003)
Year FE	Yes	Yes	Yes
Observations	49810	49810	44123
F	45.62	45.99	47.93

This table reports the slope estimates from the second stage of a 2SLS regression of banks' insured deposit ratio on digital platform adoption, instrumented via banks' AT&T exposure. In Column (1), controls include the lagged dependent variable, banks' overall coverage exposure, banks' lagged number of markets with branches, as well as a year fixed effect. In Column (2), controls additionally include logged first differences of four measures of local economic and business growth (described in Section III). The sample period is from 2010 to 2019. Observations are at the bank-year level. Standard errors are clustered at the bank level and reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 6 Insured Deposits and Business Payroll

	Insured Deposit Ratio	
	(1)	(2)
Payroll × Digital	-0.013***	-0.012***
	(0.004)	(0.004)
Payroll	0.003	0.001
	(0.003)	(0.003)
L.Insured Deposit Ratio	0.643***	0.644***
	(0.016)	(0.016)
Log Change Payroll		0.003
		(0.005)
Log Change Establishments		0.001
		(0.005)
Log Change Employment		-0.007
		(0.005)
Log Change Dep Growth		-0.003
		(0.005)
Year FE	Yes	Yes
Bank FE	Yes	Yes
Observations	44012	43882
F	41.97	42.53

This table reports the slope estimates from the second stage of a 2SLS regression of the log of insured deposits as a ratio of all deposits on digital platform adoption, instrumented via banks' AT&T exposure. Digital platform adoption is interacted with the log of overall business payroll in bank b's markets in the prior year. All specifications include controls of the lagged dependent variable, the bank's Verizon exposure, the level effect of the business payroll interaction, and a bank and year fixed effect. Column (2) additionally controls for four measures of local economic and business growth (described in Section III). The sample period is from 2010 to 2019. Standard errors are clustered at the bank level and reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 7 Bank Low Income Mortgages in New Counties

	(1) Number	(2) Volume	(3) Avg Income Jumbo
Digital	-0.265**	-0.384**	243.518***
	(0.126)	(0.178)	(68.553)
L.Y	0.516***	0.476***	0.129***
	(0.005)	(0.005)	(0.008)
L.Br Num Markets	-0.000***	-0.000***	-0.124***
	(0.000)	(0.000)	(0.026)
Overall Coverage	0.000	0.001	-2.160***
	(0.001)	(0.001)	(0.687)
County-Year FE	Yes	Yes	Yes
Observations	58422	58422	35675
F	179.88	179.78	159.56

This table reports the slope estimates from the second stage of a 2SLS regression of measures of banks' low income loan originations on digital platform adoption, instrumented via banks' AT&T exposure. Column (1) considers the log of banks' low income mortgage origination ratio in terms of the number of loans originated within a given market. Column (2) considers the log of banks' low income mortgage origination ratio in terms of the volume of loans originated within a given market. Column (3) considers the average income of borrowers to which bank b originates jumbo mortgages in county c in year t. Controls include the lagged dependent variable, bank's overall coverage exposure, banks' lagged number of markets with branches, and a county-year fixed effect. The sample period is from 2010 to 2019, and includes only counties in which bank b does not have branches. Observations are at the bank-county-year level. Standard errors are clustered at the bank level and reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 8 Loan Applications and Rejections in New Counties

	(1) Applications	(2) Low Income Application Ratio	(3) Low Income Rejection Ratio
Digital	0.597***	-0.257***	0.763***
	(0.107)	(0.091)	(0.170)
L.Y	0.778***	0.499***	0.620***
	(0.004)	(0.005)	(0.009)
L.Br Num Markets	0.000**	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Overall Coverage	0.001	-0.000	0.001
	(0.001)	(0.001)	(0.003)
County-Year FE	Yes	Yes	Yes
Observations	164531	80331	23159
F	457.42	359.70	253.63

This table reports the slope estimates from the second stage of a 2SLS regression on measures of bank mortgage applications on digital platform adoption, instrumented via banks' AT&T exposure. Column (1) considers the log number of mortgage applications received by bank b in county m in year t. Column (2) considers the log ratio of low income mortgage applications relative to all mortgage applications received by bank b in county m in year t. Column (3) considers the log ratio of low income mortgages that are rejected relative to low income mortgages received by bank b in county m in year t. All specifications include controls for the lagged dependent variable, bank's overall coverage exposure, banks' lagged number of markets with branches, and a county-year fixed effect. Observations are at the bank-county-year level. The sample period is from 2010 to 2019, and includes only counties in which bank b does not have branches. Standard errors are clustered at the bank level and reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

B. Parameter Estimates

Table 9 Deposit Market Estimates

Panel A: Demands

Parameter	Symbol	j = Insured		j = Uninsured	
Deposit Rate	α_j^R	1.393**	(0.667)	2.259***	(0.628)
Digital Platforms, Banks above $100B	$\alpha_j^{O,100B+}$	-0.060	(0.088)	0.670**	(0.283)
Digital Platforms, Banks $10B – $100B	$\alpha_j^{O,10B-100B}$	0.214***	(0.071)	0.710***	(0.259)
Digital Platforms, Banks below $10B	$\alpha_j^{O,10B-}$	0.172***	(0.057)	0.490**	(0.205)
Branches	α_j^N	0.086***	(0.033)	0.383***	(0.094)
Lag Loan Losses	α_j^{Losses}	-0.629	(0.449)	-3.223*	(1.890)
Overall Coverage	$\alpha_j^{Coverage}$	0.001**	(0.000)	0.001	(0.001)
Lag Assets	α_j^{Assets}	0.970***	(0.009)	0.935***	(0.027)
Lag Insured Ratio	$\alpha_j^{Insured}$	1.158***	(0.028)	-5.296***	(0.108)
Local Population	$\alpha_j^{Population}$	-0.000	(0.000)	-0.000***	(0.000)

Panel B: Service Costs

Parameter	Symbol	j = Insured		j = Uninsured	
Baseline, Banks above $100B	$\phi_j^{Q,100B+}$	0.14	(0.24)	1.40	(3.10)
Baseline, Banks $10B – $100B	$\phi_j^{Q,10B-100B}$	0.85***	(0.31)	2.63	(2.32)
Baseline, Banks below $10B	$\phi_j^{Q,10B+}$	5.28**	(2.63)	-4.56	(17.40)
Digital Platforms, Banks above $100B	$\phi_j^{O,100B+}$	-0.06	(0.26)	-1.36	(3.18)
Digital Platforms, Banks $10B – $100B	$\phi_j^{O,10B-100B}$	-0.66*	(0.40)	-3.49	(3.19)
Digital Platforms, Banks below $10B	$\phi_j^{O,10B-}$	-6.51*	(3.73)	4.93	(29.76)
Branches	ϕ_j^N	-0.02***	(0.01)	0.00	(0.01)

This table reports parameter estimates for the insured and uninsured deposit market. In Panel A the coefficient for branches, α_j^N, is scaled by 1000. Standard errors are reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 10 Loan Market Estimates

Panel A: Demands

Parameter	Symbol	j = High Income		j = Low Income	
Mortgage Rate	α_j^R	-0.66***	(0.04)	-0.56***	(0.04)
Digital	α_j^O	2.27**	(1.05)	1.73	(1.34)
Branches	α_j^N	0.04***	(0.00)	0.03***	(0.00)
Local Market	α_j^{Local}	1.89***	(0.03)	1.17***	(0.03)
Overall Coverage	$\alpha_j^{Coverage}$	0.00	(0.00)	-0.00	(0.00)

Panel B: Service Costs

Parameter	Symbol	j = High Income		j = Low Income	
Digital	ϕ_j^O	-1.93***	(0.25)	-1.30***	(0.18)
Branches	ϕ_j^N	-0.01***	(0.00)	-0.00***	(0.00)
County Income	ϕ_j^{Income}	-0.00***	(0.00)	-0.00***	(0.00)

Panel C: Loan Losses

Parameter	Symbol	Estimate	S.E.
Digital, Overall	δ_O	-0.033	(0.118)
Digital, Low Income	δ_L^O	0.836*	(0.444)
Digital, High Income	δ_H^O	-0.526***	(0.196)
Branches, Overall	δ^N	-0.261*	(0.150)
Branches, Low Income	δ_L^N	0.214	(0.167)
Branches, High Income	δ_H^N	0.212	(0.153)
Lag Losses	δ_U	85.124***	(0.419)
Overall Coverage	δ_C	-0.000*	(0.000)

This table reports parameter estimates for the high and low income mortgage market. In Panel C the outcome variable, the per-unit loan loss, is scaled by 100. Standard errors are reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 11 Bank Fixed Investment Costs

	Adoption f_O	Branch f_N	Entry f_C
Estimate	407,700	25,640	164.4
Bounds (L, U)	(398,800 , 416,600)	(25,270 , 26,010)	(10.8 , 318.0)

This table reports parameter estimates for banks' investment decisions at $t = 0$. The estimation is based on 2018. The first row reports the value used as the parameter estimate, and the second row reports the upper and lower bound of the parameter estimate range.

C. Counterfactuals

Table 12 Aggregate Effect of Digital Platforms on Competition

Panel A: Consolidation and Integration

	Non-Digital Equilibrium	Digital Equilibrium	Change
HHI	0.177	0.164	-6.9%
Top Share	0.909	0.894	-1.7%
Banks in County	27.59	29.83	8.2%
Bank Branches	56.43	53.15	-5.8%

Panel B: Markups, Quantities, and Expected Consumer Surplus

	Change Adj. Markup	Change Q	Change E[CS]
Deposits	-0.3%	6.3%	15.1%
Insured	-1.0%	0%	0%
Uninsured	0.4%	15.3%	32.1%
Mortgages	-7.7%	60.3%	239.6%
High Income	-5.7%	63.3%	307.2%
Low Income	-14.2%	18.8%	26.0%
Overall			26.6%

Panel C: Bank Profits

	Change Profit
Aggregate	0%
Average, \$100B+	4.0%
Average, \$10B–\$100B	15.0%
Average, \$10B−	-44.2%

This table reports market characteristics in the equilibria without and with digital platforms, as detailed in Section VII.A and Appendix A.4.C. Panel A reports the national deposit market HHI, the "Top Share", or share of deposits provided by banks with above \$100B in assets, the number of banks in an average county, and the number of branches maintained by the average bank. Panel B reports for each market segment the change in adjusted markups, change in aggregate quantities, and change in expected consumer surplus, as well as overall change in expected consumer surplus. The adjusted markup is calculated as the markup excluding the outside option share. For mortgage markets, the average change in adjusted markup across counties is reported. Panel C reports average changes in profits for banks of different size categories, as well as the aggregate change in bank profits. In all panels, changes are calculated to be the percentage change in switching from the non-digital to the digital equilibrium.

Table 13 Financial Stability Implications of Digital Platforms

Panel A: Systemic Importance

	Sum	Insured	Uninsured	High Income	Low Income	Counties
Digital, \$100B+	4.0%	-1.4%	12.5%	44.2%	7.0%	5.1%
Digital, \$10B–\$100B	29.0%	29.1%	25.2%	60.0%	16.2%	6.9%
Digital, \$10B–	17.1%	22.3%	0.8%	70.1%	19.1%	5.3%
Non-Digital	-20.7%	0%	-38.3%	-92.4%	-47.2%	0.1%

Panel B: Credit Risk

	Total	High Income	Low Income
Bank Average	-35.2%	-53.1%	176.3%
Digital	-38.3%	-58.0%	193.8%
Non-Digital	-4.9%	-4.9%	0%
Aggregate	-37.9%	-48.4%	119.2%

Panel C: Funding Risk

Uninsured Ratio	Non-Digital Equilibrium	Digital Equilibrium	Change
Aggregate	0.41	0.45	8.5%
Digital, \$100B+	0.38	0.44	17.6%
Digital, \$10B–\$100B	0.29	0.31	7.7%
Digital, \$10B–	0.20	0.19	-3.6%
Non-Digital	0.22	0.17	-22.5%

This table reports market characteristics in the equilibria without and with digital platforms, as detailed in Section VII.A and Appendix A.4.C. Panel A reports for each bank category the average change in market share by market segment, as well as "Sum" the overall change in market share across all market segments, and "Counties", the number of counties in which the bank provides services. Market shares are calculated among banks. Panel B reports the average change in expected loan losses, split by high and low income loan originations, for the average bank, the average digital bank, the average non-digital bank, as well as aggregates for the entire banking sector. Panel C reports the average change in banks' uninsured deposits ratio for banks of different categories, as well as the aggregate change for the entire banking sector. In all panels, changes are calculated to be the percentage change in switching from the non-digital to the digital equilibrium.

Appendix

Contents

A.1. Data Appendix

A. Digital Platform Adoption Measure

A.1. Adoption by Bank Size

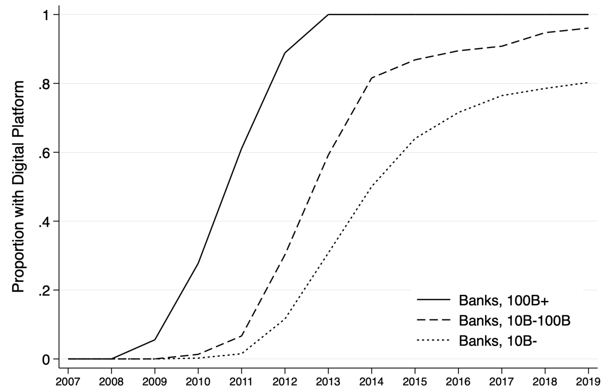
In Figure A.1 I look at bank adoption of digital platforms across the bank size distribution. The trend for banks with assets below $10 billion closely aligns with the overall trend of the banking sector, given that the majority of banks fall within this category. Banks with assets between $10 and $100 billion are faster to adopt digital platforms, with some adoption beginning in 2010 and with over 90% of these banks having digital platforms by 2019. Finally, banks with assets above $100 billion are quickest to adopt digital platforms, with some of them releasing platforms within the first year that the App stores are open, and with all of these large banks having digital platforms by 2019.

A.2. Proxy for Digital Services More Broadly

To confirm that mobile application adoption correlates with banks' digital service provision more generally, including those offered via banks' websites, I hand collect panel data on banks' website "maps" annually using the Internet Archive.[34] Specifically, I collect all the urls that are associated with a given bank's website in a given year. Figure A.2 shows examples of these maps for two banks in 2022. Notably, the site map for Chase bank is much more complex than that of Bank of the Valley.

[34] Accessible at `https://archive.org`.

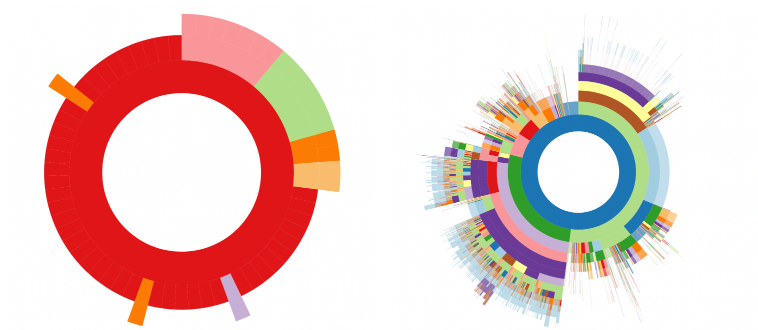
Figure A.1. Proportion of Banks with Digital Platforms: By Bank Size



This figure shows the proportion of banks that have a mobile application annually from 2005 to 2019, by bank asset size category. A bank is designated as having an application in a given year if its application was available at the beginning of that year, and has at least 5 reviews.

Figure A.2. Examples of Banks' Website Maps in 2022

Bank of the Valley Chase



This figure shows examples of banks' website "maps" in 2022 for Bank of the Valley and Chase Bank. A website "map" is the set of all urls that are associated with a given bank's website in a given year. These "maps" are retrieved from https://archive.org, where it states that the "map" feature "groups all the archives we have for websites by year, then builds a visual site map, in the form of a radial-tree graph, for each year. The center circle is the root of the website and successive rings moving out from the center present pages from the site."

Table A.1 below shows that within-bank, a banks' website becomes more complex, as measured by the log number of distinct urls, on the year that the bank develops a mobile application.

Table A.1 Website Size and Application Existence

	Website Size	
	(1)	(2)
Year App Released	0.21***	0.05***
	(0.02)	(0.02)
Bank FE	Yes	Yes
Year FE	No	Yes
Observations	56368	56368
Adjusted R^2	0.410	0.527

This table reports the slope estimates from a regression of an indicator variable tracking the first year that banks adopt a mobile application on the log number of URLs that are associated with their website in that given year. Both specifications include a bank fixed effect, and column (2) additionally includes a year fixed effect. Observations are at the bank-year level. The sample period is from 2010 to 2019. Standard errors are clustered at the bank level and reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

A.3. Services Offered

In Figure A.3, I reproduce a 2021 S&P Global survey that asks banking customers which features available on their mobile banking applications they value most. In Figure A.4, I plot banks' average application rating as a function of their log assets. I absorb a county fixed effect, comparing only banks that have branches in the same county, to control for differences in customer preferences that vary by region. I find that this relationship is increasing in bank size.

Figure A.3. S&P Global U.S. Mobile Banking Survey (2021): Which features currently available on your bank's mobile banking app do you consider most valuable?

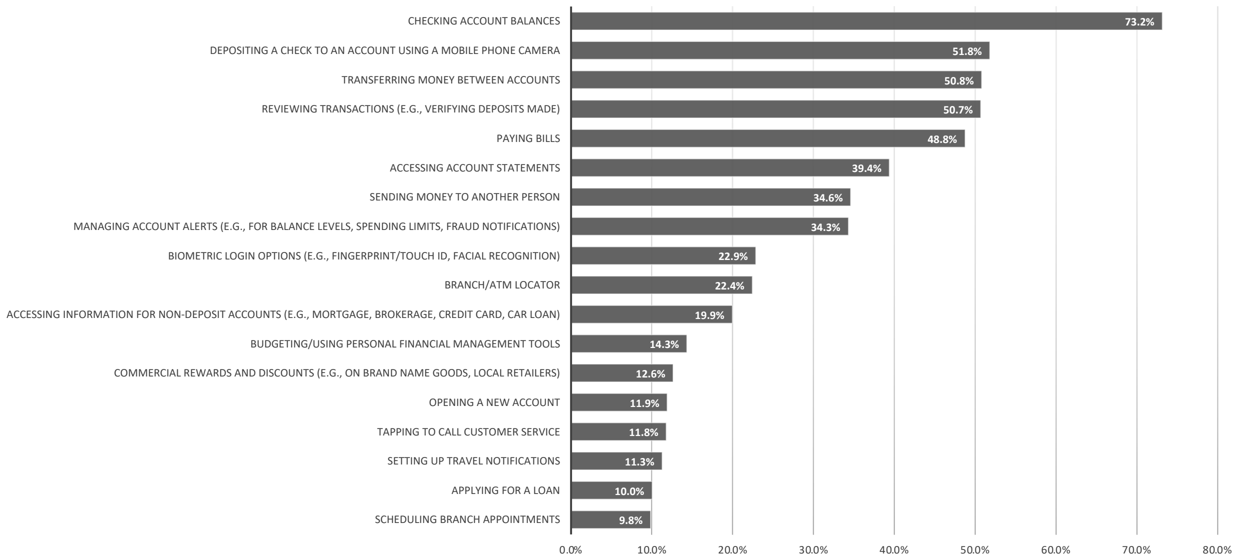
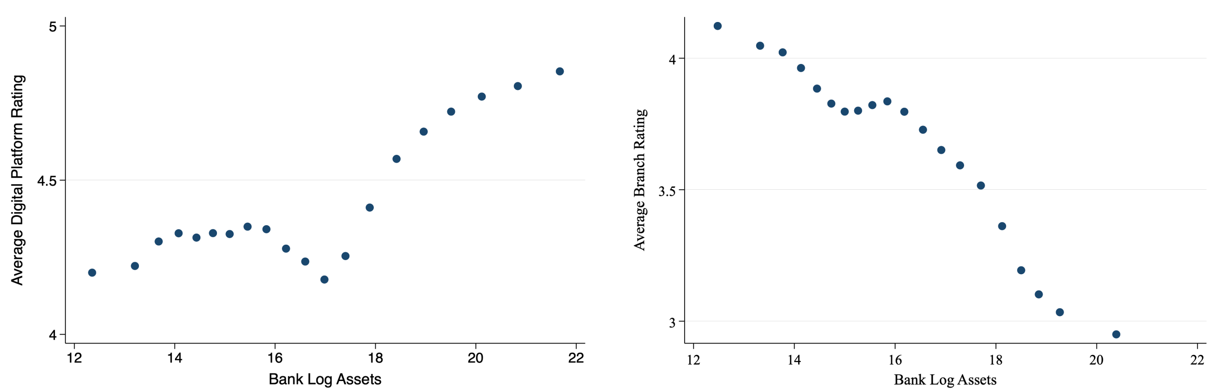


Figure A.4. Service Quality and Bank Size

Panel A plots a cross-sectional binscatter comparing comparing banks' average mobile application rating to their asset size. Panel B instead considers banks' average branch rating. Both specifications include a county FE, comparing only banks that have a branch within the same county. Application data is hand-collected. Data on banks' asset size come from 2019 from their Call Reports, branch ratings are calculated over the entire universe of hand-collected reviews, and the number of features is constructed by categorizing text strings that appear in application descriptions.

Panel A: Digital Platforms

Panel B: Branches



B. Other Data

Branches. I complement the information on banks' digital platform adoption with data on banks' physical branch networks. I obtain data on annual county-level branches and deposit volumes for each bank from the FDIC Survey of Deposits. Additionally, I hand-collect publicly available online branch reviews, obtaining 700,000 reviews for 60,000 bank branches posted on Google from 2010 through 2021.

Bank Characteristics. To build annual bank-level characteristics, balance sheet variables, and controls, I collect banks' balance sheet information from the FFIEC Consolidated Reports of Condition and Income, generally referred to as Bank Call Reports. These regulatory filings provide quarterly bank-level information for every U.S. commercial bank. Additionally, I retrieve banks' uninsured deposits from the SDI. I winsorize banks' loan loss ratio throughout the analaysis, as well as all variables constructed for the loan loss estimation regression in Section VI.B, at 2%.

Table A.2 Summary Statistics: Bank Characteristics

	Mean	sd	p25	p50	p75
Asset Growth	0.050	0.093	0.005	0.036	0.075
Deposit Growth	0.049	0.098	0.002	0.036	0.078
Insured Deposits Ratio	0.800	0.122	0.744	0.823	0.885
Low Income Loan Originations Ratio	0.182	0.143	0.077	0.160	0.262
Loan Loss Ratio	0.002	0.004	0.000	0.001	0.002
Markets with Branches	3	4	1	2	3
Mortgage Markets	17	24	5	9	17
Small Business Loan Markets	82	155	14	31	70

This table reports summary statistics for bank-level outcomes.

Deposit Rates. Banks' deposit rates are from RateWatch. I take banks' average savings rate for deposit products with minimum quantities less than $100,000 to be their insured deposit rate in a given year. I take banks' average 12-month CD rate for deposit products with minimum quantities above $100,000 to be their uninsured deposit rate in a given year. I choose $100,000 to be the cutoff rather than $250,000 to attain average deposit rates that reflect mainly insured versus uninsured deposit accounts while also maintaining sufficient coverage of banks in the sample: over 95% of banks' reported account types in a given year in the RateWatch data have minimum balances of $100,000 or less.

Mortgage Originations. I obtain mortgage origination information from the Home Mortgage Disclosure Act (HMDA). Beginning in 2017, HMDA data also includes information on individual mortgage rates for a subset of lenders. Any depository institution with a home office or branch in a Central Business Statistical Area (CBSA) is required to report to HMDA if it has made or refinanced a mortgage and if it has assets above $30 million. I focus on on-balance-sheet activity to capture lending for which bank monitoring and screening is likely to be more important. Specifically, I keep HMDA mortgages that are originated for the purpose of purchasing a home, and not sold off to any government agency during the first calendar year. I winsorize the average income of banks' jumbo borrowers in a given county at 1%.

Small Business Loan Originations. I obtain small business loan origination information from the 1977 Community Reinvestment Act's disclosure statement data.

Mobile Coverage I obtain data on mobile and broadband data coverage annually by provider at the census block level in 2015 from the FCC form F477, which collects data on the coverage provided by different carriers. I use this data to construct an instrument for digital platform adoption, as described in Section III. Throughout the analysis I winsorize the instrument and related control variables annually at 5% unless otherwise noted.

County Demographics. I retrieve additional county characteristics from the Census.

Timeseries Variables. From FRED I retrieve the Federal funds rate and deposit market size.

FinTech Presence. I obtain county level FinTech mortgage lending shares in 2015 from the dataset provided by Fuster et al. (2019).

A.2. Additional Reduced Form Results

A. Dynamic Effects

In this section I consider the effects of digital platform adoption k years in the future, for k between 0 and 3, by estimating 2SLS regressions of the form,

$$\begin{aligned} \textit{First Stage:} \quad & \text{Digital}_{b,t} = \delta_1 Z_b + \delta_2 \text{Coverage}_b + \delta_3 X_{b,t} + \eta_{b,t} \\ \textit{Second Stage:} \quad & \text{Y}_{b,t+k} = \beta_1 \widehat{\text{Digital}}_{b,t} + \beta_2 \text{Coverage}_b + \beta_3 X_{b,t} + \varepsilon_{b,t}. \end{aligned}$$

Table A.3 Geographic Expansion

	(1)	(2)	(3)	(4)
	t	$t+1$	$t+2$	$t+3$
Digital	1.01**	1.24**	1.74**	2.44*
	(0.43)	(0.55)	(0.87)	(1.41)
Overall Coverage	0.00**	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
L.Y	0.70***	0.71***	0.64***	0.58***
	(0.03)	(0.04)	(0.06)	(0.09)
L.Br Num Markets	0.01**	0.01	0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.02)
Year FE	Yes	Yes	Yes	Yes
Observations	23543	20785	17914	15150
F	27.06	22.69	14.85	9.06

This table reports the dynamic specifications associated with Table 2.

Table A.4 Branch Response

	Num Markets				Within-Market			
	t	$t+1$	$t+2$	$t+3$	t	$t+1$	$t+2$	$t+3$
Digital	-0.007	-0.005	0.009	0.024	-0.057**	-0.102*	-0.159**	-0.218**
	(0.024)	(0.050)	(0.083)	(0.125)	(0.029)	(0.053)	(0.077)	(0.105)
Overall Coverage	0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
L.Num Markets	0.997***	0.994***	0.988***	0.982***	0.000	0.000	0.000	0.000
	(0.004)	(0.008)	(0.013)	(0.019)	(0.000)	(0.000)	(0.000)	(0.000)
L. Within-Market					0.984***	0.969***	0.955***	0.942***
					(0.002)	(0.003)	(0.005)	(0.007)
FE	Year	Year	Year	Year	County-Year	County-Year	County-Year	County-Year
Observations	50357	44480	38913	33581	212798	184603	158348	133999
F	177.45	157.13	134.39	107.04	314.79	279.38	247.06	207.22

This table reports the dynamic specifications associated with Table 3.

Table A.5 Growth

	Asset Growth				Deposit Growth			
	t	$t+1$	$t+2$	$t+3$	t	$t+1$	$t+2$	$t+3$
Digital	-0.01	-0.01	0.02	0.06**	-0.01	-0.01	0.02	0.07**
	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)
L.Y	0.47***	0.26***	0.19***	0.13***	0.42***	0.21***	0.16***	0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Overall Coverage	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49463	43633	38090	32763	49373	43552	38018	32700
F	149.48	132.83	114.41	91.93	148.03	131.30	113.03	90.99

This table reports the dynamic specifications associated with overall bank growth, i.e. the specifications of Table 4 without interactions with bank size.

Table A.6 Growth by Bank Size

	Asset Growth				Deposit Growth			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	t	$t+1$	$t+2$	$t+3$	t	$t+1$	$t+2$	$t+3$
Digital, \$100B+	-0.00	-0.01	-0.01	-0.00	0.01	0.00	0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Digital, \$10B – \$100B	0.04***	0.03**	0.04**	0.05***	0.04***	0.03**	0.04***	0.06***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Digital, \$10B–	-0.01	-0.01	0.02	0.06*	-0.01	-0.01	0.02	0.07**
	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)
Overall Coverage	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L.Y	0.46***	0.25***	0.19***	0.13***	0.42***	0.21***	0.16***	0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49463	43633	38090	32763	49373	43552	38018	32700
F	48.35	42.95	36.97	29.63	47.87	42.46	36.52	29.31

This table reports the dynamic specifications associated with Table 4.

Table A.7 Insured Deposits Ratio

	(1)	(2)	(3)	(4)
	t	$t+1$	$t+2$	$t+3$
Digital	0.005	0.008	0.001	-0.015
	(0.008)	(0.016)	(0.023)	(0.034)
Overall Coverage	-0.000***	-0.000***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
L.Insured Deposit Ratio	0.947***	0.902***	0.896***	0.910***
	(0.011)	(0.021)	(0.026)	(0.034)
Year FE	Yes	Yes	Yes	Yes
Observations	49810	43968	38431	33112
F	139.27	122.82	105.17	84.04

This table reports the dynamic specifications associated with overall insured deposits ratio, i.e. Table 5 without interactions with bank size.

Table A.8 Insured Deposits Ratio by Bank Size

	Insured Deposits			
	(1)	(2)	(3)	(4)
	t	$t+1$	$t+2$	$t+3$
Digital, \$100B+	-0.02**	-0.04**	-0.07**	-0.12***
	(0.01)	(0.02)	(0.03)	(0.04)
Digital, \$10B – \$100B	-0.02***	-0.06***	-0.10***	-0.17***
	(0.01)	(0.02)	(0.03)	(0.05)
Digital, \$10B–	0.01	0.01	0.00	-0.01
	(0.01)	(0.02)	(0.02)	(0.03)
Overall Coverage	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
L.Insured Deposit Ratio	0.94***	0.90***	0.89***	0.90***
	(0.01)	(0.02)	(0.03)	(0.04)
Year FE	Yes	Yes	Yes	Yes
Observations	49810	43968	38431	33112
F	45.62	40.26	34.47	27.50

This table reports the dynamic specifications associated with Table 5.

Table A.9 Low Income Mortgages

	Number				Volume			
	t	$t+1$	$t+2$	$t+3$	t	$t+1$	$t+2$	$t+3$
Digital	-0.265**	-0.354**	-0.239*	-0.238	-0.384**	-0.380*	-0.262	-0.433**
	(0.126)	(0.143)	(0.144)	(0.145)	(0.178)	(0.198)	(0.195)	(0.192)
L.Y	0.516***	0.473***	0.431***	0.389***	0.476***	0.437***	0.396***	0.364***
	(0.005)	(0.006)	(0.007)	(0.008)	(0.005)	(0.006)	(0.007)	(0.008)
L.Br Num Markets	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Overall Coverage	0.000	0.001	0.001	0.002	0.001	0.001	0.000	0.003
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58422	40850	32740	26242	58422	40850	32740	26242
F	179.88	149.59	143.80	153.31	179.78	149.21	143.91	153.64

This table reports the dynamic specifications associated with Table 7.

B. Branch Closure Heterogeneity by County Demographics

In this section I explore whether branch closures are concentrated in certain counties, by considering a specification of the following form,

$$\text{Y}_{b,c,t} = \beta_1 \widehat{\text{Digital}}_{b,c,t} \cdot \text{Prop Low Income}_{c,t} + \beta_2 \text{Coverage}_{c,b} + \beta_3 X_{b,c,t} + \varepsilon_{b,c,t},$$

where Prop Low Income$_{c,t}$ is a categorical variable which tracks which tercile county c in year t falls in based on its share of overal low income loan originations,

$$\frac{\text{Low Income Loan Originations}_{c,t}}{\text{Loan Originations}_{c,t}}.$$

I find that banks close more branches in areas with low low income loan origination share, consistent with branches facilitating service provision to lower income customers.

Table A.10 Bank Branch Response by County Characteristic

	(1) Branches
Digital, Low Prop of Low Income	-0.144**
	(0.072)
Digital, Medium Prop of Low Income	-0.098
	(0.063)
Digital, High Prop of Low Income	-0.063
	(0.058)
L.Y	0.986***
	(0.004)
L.Br Num Markets	0.000
	(0.000)
Overall Coverage	-0.000
	(0.000)
County-Year FE	Yes
Observations	136258
F	43.21

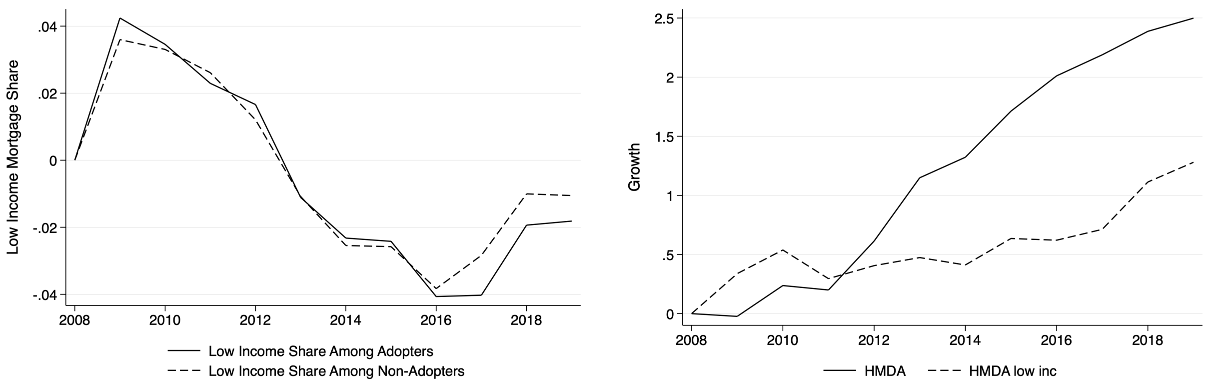
This table reports the slope estimates. Observations are at the bank-year level. The sample period is from 2010 to 2019. Standard errors are clustered at the bank level and reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

C. Aggregate Loan Effects

Figure A.5. Loan Composition

Panel A: Bank Origination Share

Panel B: Aggregate Growth



Panel A shows the annual bank-average share of low income mortgages originated, split depending on whether each bank adopted a digital platform. Bank classifications are time invariant: a bank is classified to have adopted a digital platform if it did so prior to 2014. Panel B shows the aggregate growth of overall mortgages as well as mortgages to low-income borrowers. A borrower is classified to be low income if their income is below 80% of the median MSA family income, and high income otherwise. In both figures, values are reported as growth relative to 2008, which is normalized to 0. Mortgage origination data come from HMDA.

D. Additional Loan Analysis

D.1. Guaranteed Low-Income Mortgages

While the results on low income mortgage originations in Section IV are consistent with the notion that technology may reduce banks usage of intangible information, it is important to reconcile it with literature that shows that fintech lenders are able to expand access to credit for traditionally under-served populations (e.g. Erel and Liebersohn (2022), Degerli and Wang (2022)). Importantly, I focus on on-balance-sheet lending for which banks take credit risk, whereas non-bank fintech lenders sell the majority of their originated loans, largely to government agencies (Buchak et al., 2018a). Thus, it may be that technology has different effects on lending behavior depending on whether the lenders engage in significant monitoring or screening in order to mitigate losses to loans held on balance sheet. To explore this, I look at bank lending to low-income borrowers that is guaranteed by government agencies, and may be subsequently sold off. For these government guaranteed loans, I find that the finding is reversed, consistent with this notion.

Table A.11 Guaranteed Low-Income Mortgages

	(1) Number	(2) Volume
Digital	2.664***	2.589***
	(0.388)	(0.386)
L.Y	0.584***	0.572***
	(0.022)	(0.018)
L.Br Num Markets	-0.002***	-0.002***
	(0.000)	(0.000)
Overall Coverage	0.002	0.003
	(0.002)	(0.002)
County-Year FE	Yes	Yes
Observations	32676	32676
F	83.24	96.15

This table reports the slope estimates from the second stage of a 2SLS regression on measures of banks' government-guaranteed mortgage originations to low income borrowers on digital platform adoption, instrumented via banks' AT&T exposure. Column (1) considers the log number of low income mortgages that bank b originates in county c in year t which are guaranteed by a government agency, scaled by the number of on balance sheet mortgages that the bank originates in county c in year t. Column (2) reports the analogous regression using the dollar volume of mortgage originations rather than the number. Observations are at the bank-county-year level. The sample period is from 2010 to 2019. Standard errors are clustered at the bank level and reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

D.2. Loan LTV

In this section I consider how the LTV of banks' mortgage originations changes upon adopting digital platforms, and find that they increase across the board.

Table A.12 Loan-to-Value

	(1) Overall	(2) Low Income	(3) Jumbo
Digital	21.259***	29.644***	8.125**
	(3.814)	(8.885)	(3.913)
L.Y	0.163***	0.054***	0.009**
	(0.008)	(0.004)	(0.004)
L.Br Num Markets	-0.009***	-0.013***	-0.003***
	(0.001)	(0.001)	(0.001)
Overall Coverage	0.079***	0.137***	0.039
	(0.017)	(0.030)	(0.042)
County-Year FE	Yes	Yes	Yes
Observations	42117	20345	10770
F	258.18	73.61	168.87

This table reports the slope estimates from the second stage of a 2SLS regression on measures of banks' average LTV on originated mortgages on digital platform adoption, instrumented via banks' AT&T exposure. Column (1) considers the average LTV of all borrowers to which bank b originates jumbo mortgages in county c in year t, and column (2) reports the analogous regression considering only the average LTV of low income borrowers, and column (3) for jumbo mortgage borrowers. Observations are at the bank-county-year level. The sample period is from 2018 to 2019, the period during which HMDA collects LTV information. Standard errors are clustered at the bank level and reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

A.3. Reduced Form Robustness

A. Instrument Details

A.1. Maps

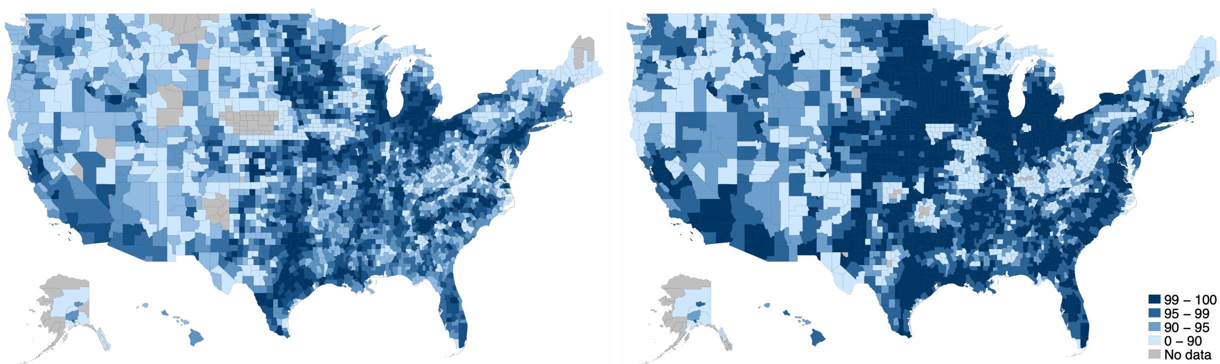
Figure A.6 shows the seven "Baby Bells" that were created following *United States v. AT&T*, the 1974 Department of Justice lawsuit which broke up the monopoly of Bell Labs. The company known as AT&T today was originally the Southwestern Bell Corporation, while Verizon was Bell Atlantic. Figure A.7 shows county-level AT&T and Verizon LTE coverage in 2015.

Figure A.6. "Baby Bells" Map

Source: Bell System Memorial (link)

Figure A.7. AT&T and Verizon Coverage Maps

AT&T Verizon



Source: FCC Form F477 (2015)

A.2. Covariate Balance

Table A.13 Covariate Balance in 2009

	ATT Coverage				
	(1)	(2)	(3)	(4)	(5)
Deposit Growth	0.00				
	(0.00)				
Asset Growth		-0.00			
		(0.00)			
Insured Deposit Ratio			-0.00		
			(0.01)		
HMDA Markets				-0.00	
				(0.00)	
Markets with Branches					0.00
					(0.00)
Lag Markets with Branches				-0.00***	
				(0.00)	
L.Y	-0.00	-0.00	-0.00	0.00**	-0.00
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Overall Coverage	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.16***	0.16***	0.16***	0.24***	0.16***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	5311	5320	5405	2313	5419
Adjusted R^2	0.672	0.672	0.674	0.620	0.674

This table reports the slope estimates of banks' AT&T coverage exposure on bank-level outcome variables of interest. Observations are at the bank level in 2009, prior to the introduction of digital service platforms. Standard errors are reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

A.3. Demographic Balance

Table A.14 Instrument Demographic Balance

	ATT Coverage	
	(1)	(2)
Prop Over 60	-0.26***	-0.11***
	(0.02)	(0.01)
Median Income	-0.00	-0.02***
	(0.00)	(0.00)
Prop Urban	0.07***	0.01***
	(0.00)	(0.00)
Overall Coverage		0.00***
		(0.00)
Constant	0.97***	0.38***
	(0.04)	(0.03)
Observations	7454	7454
Adjusted R^2	0.221	0.692

This table reports the slope estimates of banks' AT&T coverage exposure on banks' exposure to various demographics. Demographic variables are computed analogously to AT&T coverage exposure, using data from the 2010 census. Observations are at the bank level. Standard errors are reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

A.4. Android Smartphones

Although the Android operating system led by Samsung smartphones later increased in capability and popularity, in early years the iPhone dominated the smartphone industry in the United States. By the end of 2010, "Apple had completely controlled the high-end smartphone market for three years" (Vogelstein, 2013). Thus, despite several Android releases, as well as the release of Google's Android Market (now Google Play) in October of 2008, it was largely Apple's iPhone and App Store that inspired companies to develop digital applications.[35] Further, Android's market share remained below 10% until late 2010.[36]

[35] One year after the release of the iTunes App Store, it hosted 50,000 unique applications that had collectively been downloaded over 1.5 billion times. Sources: https://techcrunch.com/2009/06/08/40-million-iphones-and-ipod-touches-and-50000-apps/ ; https://www.engadget.com/2009/07/14/apples-app-store-crosses-the-1-5-billion-download-mark/

[36] Source: https://www.engadget.com/2011-12-14-shocker-android-grew-us-market-share-after-q2-ios-was-static.html

A.5. Additional Threats to Identification

One concern may be that the development of digital platform technologies coincides with the Great Financial Crisis of 2008 as well as the subsequent changes in the regulatory framework of the banking system. As a result, one may worry that the effects which I attribute to digital technology arise in fact due to repercussions of the crisis. For instance, it is important to understand whether the mergers and the consolidation of the banking sector that took place after the crisis explain any differential bank growth that I observe. Further, one may wonder whether changes in deposit composition can be explained by the post crisis regulations which increased deposit insurance ceiling from $100,000 to $250,000. Similarly on the asset side, the collapse of the subprime securitization market likely alters banks' incentives to originate mortgages across the distribution of borrowers. In fact, my instrument is precisely geared to help with this identification concern: it uses purely cross-sectional variation for identification, and I include a year fixed effect in all specifications to absorb out time series effects. Further, this cross-sectional variation allows me to exclude the crisis period from my sample: I start my IV analyses in 2010, after the crisis and the merger activity. In order for any results to be explained by the crisis, it would have to be that banks with higher AT&T exposure were differentially exposed to the crisis, conditional on their overall coverage exposure. I look at bank outcomes during the crisis period 2008-09, and show that banks with high exposure to my instrument did not exhibit differential trends in these outcomes during the crisis, confirming that this is not the case.

Another concern may be that the data for cellular coverage is measured in 2015, which is after the period of AT&T exclusivity that ended in 2012. This prompts the concern that using cellular coverage from a later time period introduces endogeneity issues, as subsequent changes in coverage need not be random. However, in practice cellular coverage is quite persistent, and by controlling for overall coverage, which includes Verizon coverage, I account for contemporaneous incentives that affect both major cellular providers. Further, changes in cellular coverage are not a concern as long as the cellular industry is not responding to the behavior of the banking industry.

B. Demographic Differences

Table A.15 Expansion

	(1)	(2)	(3)	(4)
	t	$t+1$	$t+2$	$t+3$
Digital	0.90**	1.24**	1.81*	2.69
	(0.45)	(0.63)	(1.09)	(2.05)
Overall Coverage	0.00	0.00*	0.00*	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
L.Y	0.70***	0.71***	0.64***	0.57***
	(0.03)	(0.04)	(0.07)	(0.12)
L.Br Num Markets	0.02**	0.01	0.01	-0.00
	(0.01)	(0.01)	(0.02)	(0.03)
Prop Over 60	0.06	0.05	0.03	0.14
	(0.23)	(0.31)	(0.45)	(0.73)
Prop Urban	0.08*	0.00	-0.03	-0.08
	(0.04)	(0.06)	(0.10)	(0.18)
Median Income	-0.05	-0.05	-0.05	-0.06
	(0.03)	(0.04)	(0.06)	(0.09)
Year FE	Yes	Yes	Yes	Yes
Observations	23543	20785	17914	15150
F	21.11	16.97	9.97	4.94

This table reports the dynamic specification with demographic controls associated with Table 2.

Table A.16 Growth by Bank Size with Demographic Controls

	Asset Growth				Deposit Growth			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	t	$t+1$	$t+2$	$t+3$	t	$t+1$	$t+2$	$t+3$
Digital, \$100B+	-0.01	-0.02*	-0.02*	-0.02	0.00	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Digital, \$10B – \$100B	0.03**	0.01	0.02	0.03	0.04**	0.02	0.02	0.04*
	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Digital, \$10B–	-0.02	-0.02	-0.00	0.03	-0.02	-0.02	0.00	0.04
	(0.02)	(0.03)	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.04)
Overall Coverage	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L.Y	0.46***	0.26***	0.19***	0.13***	0.42***	0.21***	0.16***	0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Prop Urban	0.01**	0.01***	0.02***	0.02***	0.01**	0.01***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Prop Over 60	0.01	0.00	-0.01	-0.02	0.00	0.01	-0.01	-0.01
	(0.02)	(0.03)	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.04)
Median Income	0.00	0.01***	0.02***	0.02***	0.00	0.01**	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49463	43633	38090	32763	49373	43552	38018	32700
F	28.10	24.89	21.37	16.92	27.83	24.61	21.12	16.74

This table reports the dynamic specification with demographic controls associated with Table 4.

Table A.17 Insured Deposits Ratio by Size

	Insured Deposits			
	(1)	(2)	(3)	(4)
	t	$t+1$	$t+2$	$t+3$
Digital, \$100B+	-0.01	-0.02	-0.04	-0.07
	(0.01)	(0.02)	(0.03)	(0.04)
Digital, \$10B – \$100B	-0.01	-0.03	-0.06*	-0.10**
	(0.01)	(0.02)	(0.03)	(0.05)
Digital, \$10B–	0.02*	0.05**	0.07**	0.10*
	(0.01)	(0.02)	(0.04)	(0.05)
Overall Coverage	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
L.Insured Deposit Ratio	0.94***	0.90***	0.89***	0.90***
	(0.01)	(0.02)	(0.03)	(0.03)
Prop Over 60	0.02*	0.05**	0.08**	0.11**
	(0.01)	(0.02)	(0.03)	(0.05)
Median Income	-0.00	-0.00	-0.00	-0.01
	(0.00)	(0.00)	(0.01)	(0.01)
Prop Urban	-0.01***	-0.02***	-0.04***	-0.05***
	(0.00)	(0.00)	(0.01)	(0.01)
Year FE	Yes	Yes	Yes	Yes
Observations	49810	43968	38431	33112
F	28.54	25.14	21.55	17.15

This table reports the dynamic specification with demographic controls associated with Table 5.

C. OLS and Two-Way Fixed Effect Regressions

Table A.18 Branch Response

	Num Markets		Within-Market	
	(1)	(2)	(3)	(4)
Digital	0.019***	0.016***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
L. Num Markets	0.993***	0.733***	-0.000**	-0.000***
	(0.001)	(0.007)	(0.000)	(0.000)
L. Within-Market			0.981***	0.971***
			(0.001)	(0.001)
FE	Year	Year & Bank	County-Year	County-Year & Bank
Observations	50357	50048	214553	214383
Adjusted R2	0.972	0.976	0.98	0.98

This table reports the OLS and TWFE specifications associated with Table 3.

Table A.19 Bank Expansion: Mortgages

	(1)	(2)	(3)	(4)
Digital	0.06***	0.04***	0.05***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)
L.Y	0.77***	0.31***	0.76***	0.31***
	(0.01)	(0.01)	(0.01)	(0.01)
L.Br Num Markets	0.03***	0.04***	0.03***	0.04***
	(0.00)	(0.00)	(0.00)	(0.00)
Nonbank Fintech Exposure	-0.15		-0.20	
	(0.15)		(0.15)	
Prop Over 60			-0.00	20.11*
			(0.13)	(11.83)
Median Income			-0.04**	0.30
			(0.02)	(1.46)
Prop Urban			0.14***	146.68***
			(0.01)	(50.40)
Year FE	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes
Observations	23543	23291	23543	23291
Adjusted R2	0.82	0.88	0.82	0.88

This table reports the OLS and TWFE specifications associated with Table 2.

Table A.20 Bank Growth: OLS

	Asset Growth			Deposit Growth		
	(1)	(2)	(3)	(4)	(5)	(6)
Digital	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L.Y	0.46***	0.45***	0.45***	0.41***	0.41***	0.41***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Nonbank Fintech Exposure	-0.08***	-0.08***	-0.06***	-0.08***	-0.08***	-0.07***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Est. Growth		0.03***	0.03***		0.03***	0.03***
		(0.01)	(0.01)		(0.01)	(0.01)
Emp. Growth		-0.01***	-0.01***		-0.01***	-0.01***
		(0.00)	(0.00)		(0.00)	(0.00)
Payroll Growth		0.01**	0.01**		0.01**	0.01**
		(0.00)	(0.00)		(0.00)	(0.00)
Deposit Growth		0.06***	0.06***		0.06***	0.06***
		(0.01)	(0.01)		(0.01)	(0.01)
Prop Over 60			0.03*			0.03*
			(0.01)			(0.02)
Median Income			0.01***			0.01***
			(0.00)			(0.00)
Prop Urban			0.01***			0.01***
			(0.00)			(0.00)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49463	43894	43894	49373	43813	43813
Adjusted R2	0.24	0.25	0.25	0.20	0.22	0.22

This table reports the OLS specifications associated with Table 4 for overall growth without bank-size interactions.

Table A.21 Bank Growth: Two-way FE

	Asset Growth			Deposit Growth		
	(1)	(2)	(3)	(4)	(5)	(6)
Digital	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L.Y	0.23***	0.21***	0.21***	0.21***	0.18***	0.18***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Est. Growth		0.03***	0.03***		0.03***	0.03**
		(0.01)	(0.01)		(0.01)	(0.01)
Emp. Growth		-0.01***	-0.01***		-0.01***	-0.01***
		(0.00)	(0.00)		(0.00)	(0.00)
Payroll Growth		0.01**	0.01**		0.01**	0.01**
		(0.00)	(0.00)		(0.00)	(0.00)
Deposit Growth		0.05***	0.05***		0.06***	0.06***
		(0.01)	(0.01)		(0.01)	(0.01)
Prop Over 60			8.14***			7.94***
			(2.14)			(2.34)
Median Income			0.01			-0.19
			(0.29)			(0.31)
Prop Urban			-28.85			-51.39**
			(20.86)			(20.02)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49176	43676	43676	49086	43595	43595
Adjusted R2	0.31	0.31	0.31	0.27	0.28	0.28

This table reports the TWFE specifications associated with Table 4 for overall growth without bank-size interactions.

Table A.22 Bank Growth by Size: OLS

	Asset Growth			Deposit Growth		
	(1)	(2)	(3)	(4)	(5)	(6)
Digital, \$100B+	0.01*	-0.00	-0.00	0.02***	0.01	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Digital, \$10B – \$100B	0.04***	0.04***	0.03***	0.04***	0.04***	0.04***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Digital, \$10B–	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L.Y	0.46***	0.45***	0.45***	0.41***	0.41***	0.41***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Est. Growth		0.03***	0.03***		0.03***	0.03***
		(0.01)	(0.01)		(0.01)	(0.01)
Emp. Growth		-0.01***	-0.01***		-0.01***	-0.01***
		(0.00)	(0.00)		(0.00)	(0.00)
Payroll Growth		0.01**	0.01**		0.01**	0.01**
		(0.00)	(0.00)		(0.00)	(0.00)
Deposit Growth		0.06***	0.06***		0.06***	0.06***
		(0.01)	(0.01)		(0.01)	(0.01)
Prop Over 60			0.02			0.03*
			(0.01)			(0.02)
Median Income			0.01***			0.01***
			(0.00)			(0.00)
Prop Urban			0.01***			0.01***
			(0.00)			(0.00)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49463	43894	43894	49373	43813	43813
Adjusted R2	0.24	0.25	0.25	0.20	0.22	0.22

This table reports the OLS specifications associated with Table 4.

Table A.23 Bank Growth by Size: Two-way FE

	Asset Growth			Deposit Growth		
	(1)	(2)	(3)	(4)	(5)	(6)
Digital, \$100B+	-0.00	0.00	0.00	-0.01	-0.02	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Digital, \$10B – \$100B	0.02	0.02^{**}	0.02^{**}	0.01	0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Digital, \$10B–	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L.Y	0.23^{***}	0.21^{***}	0.21^{***}	0.21^{***}	0.18^{***}	0.18^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Est. Growth		0.03^{***}	0.03^{***}		0.03^{***}	0.03^{**}
		(0.01)	(0.01)		(0.01)	(0.01)
Emp. Growth		-0.01^{***}	-0.01^{***}		-0.01^{***}	-0.01^{***}
		(0.00)	(0.00)		(0.00)	(0.00)
Payroll Growth		0.01^{**}	0.01^{**}		0.01^{**}	0.01^{**}
		(0.00)	(0.00)		(0.00)	(0.00)
Deposit Growth		0.05^{***}	0.05^{***}		0.06^{***}	0.06^{***}
		(0.01)	(0.01)		(0.01)	(0.01)
Prop Over 60			8.18^{***}			7.99^{***}
			(2.14)			(2.34)
Median Income			0.01			-0.19
			(0.30)			(0.31)
Prop Urban			-28.63			-51.55^{***}
			(20.87)			(19.84)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49176	43676	43676	49086	43595	43595
Adjusted R2	0.31	0.31	0.31	0.28	0.28	0.28

This table reports the TWFE specifications associated with Table 4.

Table A.24 Insured Deposits Ratio

	(1)	(2)	(3)	(4)	(5)	(6)
Digital	-0.005***	-0.003**	-0.004***	-0.003**	-0.003***	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
L.Insured Deposit Ratio	0.946***	0.644***	0.972***	0.668***	0.968***	0.665***
	(0.011)	(0.015)	(0.008)	(0.013)	(0.009)	(0.013)
Log Change Establishments			0.002	-0.002	0.002	-0.001
			(0.004)	(0.004)	(0.004)	(0.004)
Log Change Employment			0.004	0.003	0.004	0.003
			(0.003)	(0.002)	(0.003)	(0.003)
Log Change Payroll			-0.004	-0.002	-0.005	-0.002
			(0.003)	(0.003)	(0.003)	(0.003)
Log Change Dep Growth			-0.011***	-0.004	-0.010***	-0.005
			(0.003)	(0.004)	(0.003)	(0.004)
Prop Over 60					0.014*	-5.682***
					(0.008)	(1.231)
Median Income					-0.002	0.146
					(0.001)	(0.175)
Prop Urban					-0.010***	86.972***
					(0.001)	(17.428)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes
Observations	49810	49506	44123	43882	44123	43882
Adjusted R2	0.89	0.91	0.90	0.92	0.90	0.92

This table reports the OLS and TWFE specifications associated with Table 5 for overall insured deposits ratio without bank-size interactions.

Table A.25 Insured Deposits Ratio by Bank Size

	(1)	(2)	(3)	(4)	(5)	(6)
Digital, \$100B+	-0.026***	-0.063**	-0.019**	-0.066*	-0.017**	-0.063*
	(0.008)	(0.029)	(0.007)	(0.035)	(0.008)	(0.036)
Digital, \$10B – \$100B	-0.029***	-0.051***	-0.021***	-0.047***	-0.018***	-0.047***
	(0.008)	(0.015)	(0.007)	(0.012)	(0.007)	(0.012)
Digital, \$10B−	-0.004***	-0.002	-0.003***	-0.002**	-0.002***	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
L.Insured Deposit Ratio	0.943***	0.642***	0.970***	0.666***	0.966***	0.662***
	(0.011)	(0.015)	(0.008)	(0.013)	(0.009)	(0.013)
Log Change Establishments			0.002	-0.001	0.002	-0.001
			(0.005)	(0.004)	(0.004)	(0.004)
Log Change Employment			0.004	0.003	0.004	0.003
			(0.003)	(0.002)	(0.003)	(0.003)
Log Change Payroll			-0.004	-0.002	-0.005	-0.002
			(0.003)	(0.003)	(0.003)	(0.003)
Log Change Dep Growth			-0.011***	-0.005	-0.010***	-0.005
			(0.003)	(0.004)	(0.003)	(0.004)
Prop Over 60					0.015*	-5.737***
					(0.008)	(1.241)
Median Income					-0.002	0.165
					(0.001)	(0.175)
Prop Urban					-0.010***	86.041***
					(0.001)	(17.431)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes
Observations	49810	49506	44123	43882	44123	43882
Adjusted R2	0.89	0.91	0.90	0.92	0.90	0.92

This table reports the OLS and TWFE specifications associated with Table 5.

Table A.26 Low Income Mortgages

	Number		Volume		Avg Income Jumbo	
	(1)	(2)	(3)	(4)	(5)	(6)
Digital	-0.007	0.032***	-0.017*	0.048***	0.017	0.016
	(0.007)	(0.010)	(0.010)	(0.014)	(0.013)	(0.018)
L.Y	0.527***	0.391***	0.491***	0.351***	0.242***	0.083***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)
L.Br Num Markets	-0.000***	-0.000***	-0.001***	-0.001***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes
Observations	59226	58775	59226	58775	23812	23484
Adjusted R2	0.43	0.48	0.41	0.47	0.25	0.35

This table reports the OLS and TWFE specifications associated with Table 7.

A.4. Model Details

A. Details for $t = 1$

A.1. Bank Balance Sheet

The bank operates subject to its balance sheet identity, Equation 1,

$$Q_b^{A,0} + Q_b^{A,1} + \sum_{c \in \mathcal{C}_b} Q_{bc}^L + \sum_{c \in \mathcal{C}_b} Q_{bc}^H = Q_b^{E,0} + Q_b^{E,1} + Q_b^{DI} + Q_b^{DU} + Q_b^W \tag{1}$$

Its balance sheet has quantity $Q_b^{A,0}$ of pre-existing long-term assets that earn a net return R_b^0.[37] I assume that other new assets $Q_b^{A,1}$ earn the Fed funds rate f.[38] It also has quantity $Q_b^{E,0}$ of book equity, and it can increase its equity through retained earnings $Q_b^{E,1}$. In addition to deposits, the bank can obtain wholesale funding Q_b^W, again at the Fed funds rate f.[39]

As a result, banks' profit maximization at $t = 1$ is equal to,

$$\begin{aligned}
\max_{R^{DI}, R^{DU}, \{R_c^H\}, \{R_c^L\}} & \underbrace{\sum_{c \in \mathcal{C}_b} (R_{bc}^H - f) Q_{bc}^H (R_{bc}^H) + \sum_{c \in \mathcal{C}_b} (R_{bc}^L - f) Q_{bc}^L (R_{bc}^L)}_{\text{Local loan return}} \\
& + \underbrace{(f - R_b^{DI}) Q_b^{DI} (R_b^{DI}) + (f - R_b^{DU}) Q_b^{DU} (R_b^{DU})}_{\text{National deposit return}} - \underbrace{L(\mathcal{Q}_b)}_{\text{Losses}} - \underbrace{\Phi(\mathcal{Q}_b)}_{\text{Costs}} \\
& + (f - f) Q_b^W + (R_b^0 - f) Q_b^{A,0} + (f - f) Q_b^{A,1}
\end{aligned}$$

where maximization of this profit function is equivalent to maximizing the expression without the terms in the final row, as presented in Equation 20 of the main text.

A.2. Logit Choice Probabilities

Following Train Chapter 3, let the utility of bank b to customer i be given by $U_{i,b} = V_{i,b} + \varepsilon_{i,b}$, where $V_{i,b}$ denotes the part that is observable to the econometrician up to some parameterization, and $\varepsilon_{i,b}$ the unknown part. The probability that customer i chooses bank

[37] The maintained assumption is that the net return of existing assets R_b^0 is not affected by subsequent changes to banks' branch networks or digital platforms. This is consistent with a setting in which most monitoring and screening as well as service provision is done at the time of origination rather than afterwards.

[38] By letting other assets $Q_b^{A,1}$ earn net return f, I shut off the margin of allowing banks to have different investment opportunities apart from the retail deposit and lending markets that I model. In this case, the bank will optimally hold $Q_b^{A,1}$ only if it has excess deposits relative to its retail lending and existing assets $Q_b^{A,0}$.

[39] Note that I assume that bank deposits have zero maturity. This is supported by the literature on banks' maturity transformation (banks are funded by short term deposits)

b is given by,

$$
\begin{aligned}
P_{i,b} &= P(V_{i,b} + \varepsilon_{i,b} \geq V_{i,b'} + \varepsilon_{i,b'} | \forall b' \neq b) \\
&= P(\varepsilon_{i,b'} \leq \varepsilon_{i,b} + V_{i,b} - V_{i,b'} | \forall b' \neq b)
\end{aligned}
\tag{2}
$$

Where we have that each $\varepsilon_{i,b}$ is independently and identically distributed extreme value so that,

$$
f(\varepsilon_{i,b}) = \exp(-\varepsilon_{i,b}) \cdot \exp(-\exp(-\varepsilon_{i,b})) \tag{3}
$$

$$
F(\varepsilon_{i,b}) = \exp(-\exp(-\varepsilon_{i,b})) \tag{4}
$$

For a given $\varepsilon_{i,b'}$, Equation 2 is the CDF for each $\varepsilon_{i,b'}$ evaluated at $\varepsilon_{i,b} + V_{i,b} - V_{i,b'}$, which by Equation 4 is equal to,

$$
\exp(-\exp(-(\varepsilon_{i,b} + V_{i,b} - V_{i,b'})))
$$

Since the $\varepsilon_{i,b}$'s are all independent, the CDF over all $b' \neq b$ is the product of the individual CDFs,

$$
P_{i,b} | \varepsilon_{i,b} = \prod_{b' \neq b} \exp(-\exp(-(\varepsilon_{i,b} + V_{i,b} - V_{i,b'}))) \tag{5}
$$

And since $\varepsilon_{i,b}$ is not given, the choice probability is the integral of $P_{i,b} | \varepsilon_{i,b}$ over all values of $\varepsilon_{i,b}$, weighted by its density, Equation 3,

$$
P_{i,b} = \int_{-\infty}^{\infty} \left(\prod_{b' \neq b} \exp(-\exp(-(\varepsilon_{i,b} + V_{i,b} - V_{i,b'}))) \right) \cdot \exp(-\varepsilon_{i,b}) \cdot \exp(-\exp(-\varepsilon_{i,b})) d\varepsilon_{i,b} \tag{6}
$$

Now note that $V_{i,b} - V_{i,b} = 0$ and multiply by $1 = \dfrac{\exp(-\exp(-\varepsilon_{i,b}))}{\exp(-\exp(-\varepsilon_{i,b}))}$ to arrive at,

$$
\begin{aligned}
P_{i,b} &= \int_{-\infty}^{\infty} \left(\prod_{b' \in \mathcal{B}} \exp(-\exp(-(\varepsilon_{i,b} + V_{i,b} - V_{i,b'}))) \right) \cdot \exp(-\varepsilon_{i,b}) d\varepsilon_{i,b} \\
&= \int_{-\infty}^{\infty} \exp\left(-\sum_{b' \in \mathcal{B}} \exp(-(\varepsilon_{i,b} + V_{i,b} - V_{i,b'})) \right) \cdot \exp(-\varepsilon_{i,b}) d\varepsilon_{i,b} \\
&= \int_{-\infty}^{\infty} \exp\left(-\exp(-\varepsilon_{i,b}) \sum_{b' \in \mathcal{B}} \exp(-(V_{i,b} - V_{i,b'})) \right) \cdot \exp(-\varepsilon_{i,b}) d\varepsilon_{i,b}
\end{aligned}
$$

Now define $t = \exp(-\varepsilon_{i,b})$ so that $dt = -\exp(-\varepsilon_{i,b})d\varepsilon_{i,b}$ and note that as $\varepsilon_{i,b} \to \infty$, $t \to 0$. As $\varepsilon_{i,b} \to -\infty$, $t \to \infty$. Then,

$$\begin{aligned}
P_{i,b} &= \int_{\infty}^{0} \exp\left(-t \sum_{b' \in \mathcal{B}} \exp(-(V_{i,b} - V_{i,b'}))\right)(-dt) \\
&= \int_{0}^{\infty} \exp\left(-t \sum_{b' \in \mathcal{B}} \exp(-(V_{i,b} - V_{i,b'}))\right) dt
\end{aligned}$$

By the Fundamental Theorem of Calculus,

$$\begin{aligned}
P_{i,b} &= \left. \frac{\exp\left(-t \sum_{b' \in \mathcal{B}} \exp(-(V_{i,b} - V_{i,b'}))\right)}{-\sum_{b' \in \mathcal{B}} \exp(-(V_{i,b} - V_{i,b'}))} \right|_{t=0}^{t=\infty} \\
&= 0 - \frac{1}{-\sum_{b' \in \mathcal{B}} \exp(-(V_{i,b} - V_{i,b'}))} \\
&= \frac{\exp(V_{i,b})}{\sum_{b' \in \mathcal{B}} \exp(V_{i,b'})} \qquad (7)
\end{aligned}$$

A.3. Logit Elasticities and Semi-Elasticities

I derive elasticities of Logit market shares with respect to own-characteristics. For a characteristic $x_{jbm} \in X_{bm}$,

$$\frac{\partial s_{bm}}{\partial x_{jbm}} = \frac{\partial \dfrac{exp(\alpha_j X_{bm})}{1 + \sum_{b' \in \mathcal{B}} exp(\alpha_j X_{b'm})}}{\partial x_{jbm}} \qquad (8)$$

$$= \frac{exp(\alpha_j X_{bm})}{1 + \sum_{b' \in \mathcal{B}} exp(\alpha_j X_{b'm})} \frac{\partial \alpha_j X_{bm}}{\partial x_{jbm}} - \left(\frac{exp(\alpha_j X_{bm})}{1 + \sum_{b' \in \mathcal{B}} exp(\alpha_j X_{b'm})}\right)^2 \frac{\partial \alpha_j X_{bm}}{\partial x_{jbm}} \qquad (9)$$

$$= \frac{\partial \alpha_j X_{bm}}{\partial x_{jbm}}(s_{bm} - s_{bm}^2) \qquad (10)$$

$$= \beta_j s_{bm}(1 - s_{bm}) \qquad (11)$$

Thus the elasticity of bank b's market share with respect to bank b's characteristic x_{bm} is:

$$E = \frac{\partial s_{bm}}{\partial x_{jbm}} \frac{x_{jbm}}{s_{bm}} = \beta_j x_{jbm}(1 - s_{bm}) \qquad (12)$$

And similarly the semi-elasticity of bank b's market share with respect to bank b's characteristic x_{bm} is:

$$E = \frac{\partial s_{bm}}{\partial x_{jbm}} \frac{1}{s_{bm}} = \beta_j(1 - s_{bm}) \qquad (13)$$

Thus for infinitesimally small market share s_{bm}, β_j is the proportional change in market share of bank b for a one unit increase in x_{jbm}.

A.4. Rate First Order Conditions

Restating banks' rate choice in terms of $MR = MC$:

$$R^{*R}_m - f = \frac{\partial C}{\partial Q^R_m} - Q^R_m \left(\frac{\partial Q^R_m}{\partial R^R_m}\right)^{-1} \tag{14}$$

$$R^{*T}_m - f = \frac{\partial C}{\partial Q^T_m} - Q^T_m \left(\frac{\partial Q^T_m}{\partial R^T_m}\right)^{-1} \tag{15}$$

$$f - R^{*D_m} = \frac{\partial C}{\partial Q^D_m} + Q^D_m \left(\frac{\partial Q^D_m}{\partial R^D_m}\right)^{-1} \tag{16}$$

I can then substitute in the rate-elasticity derived above for logit demand, to arrive at:

$$R^{*R}_m - f = \frac{\partial C}{\partial Q^R_m} - \frac{1}{\alpha^R(1 - s^R_{bm})} \quad \text{where } \alpha^R < 0 \tag{17}$$

$$R^{*T}_m - f = \frac{\partial C}{\partial Q^T_m} - \frac{1}{\alpha^T(1 - s^T_{bm})} \quad \text{where } \alpha^T < 0 \tag{18}$$

$$f - R^{*D_m} = \frac{\partial C}{\partial Q^D_m} + \frac{1}{\alpha^D(1 - s^D_{bm})} \quad \text{where } \alpha^D > 0 \tag{19}$$

A.5. Derivation of Linear Demand Estimation Equation

Begin with the equation for bank market share, where $\alpha^R_j f + \xi_{i0} = 0$,

$$s^j_b = \frac{exp(\alpha_j X_b)}{exp(\alpha^R_j f + \xi_{i0}) + \sum_{b' \in \mathcal{B}} exp(\alpha_j X_{b'})} \qquad j \in \{DI, DU\}$$

Taking logs,

$$\log(s^j_b) = \alpha_j X_b - \log(1 + \sum_{b' \in \mathcal{B}} exp(\alpha_j X_{b'}))$$

$$\log(s^j_0) = -\log(1 + \sum_{b' \in \mathcal{B}} exp(\alpha_j X_{b'}))$$

$$\log(s^j_b) - \log(s^j_0) = \alpha_j X_b$$

B. Details for $t = 0$

B.1. Fixed Costs, Forward-Looking Behavior, and Hurdle Rates

Fixed adoption costs can induce forward-looking behavior. This two-stage framework is consistent with banks making technology investment decisions depending on whether the return on investment exceeds some "hurdle rate", as described in Wollmann (2018).

When a bank's capital budgeting process relies on hurdle rates, the decision rule can be written as linearly separable in first stage fixed costs and second stage profit terms. Investment decisions reflect a comparison between second stage profit changes and first stage sunk cost changes, with the sunk cost scaled by a constant— the hurdle rate. Thus for the purpose of analysis, including counterfactuals, hurdle rates do not need to be estimated and can be ignored. In estimation I estimate scaled sunk costs along with changes in profits, and compare these terms to predict technology investment decisions. Unscaled sunk cost parameters are not used. The maintained identification assumption is that hurdle rates are not changed by the counterfactual exercises.

B.2. Moment Inequality Estimation Details

If I observe that the bank has $\{O_b^*, \{B_m^*\}, \{m\}\} = d_i$, and let d_{-b} denote the Nash strategies of other players, then I assume that the *revealed preference condition* in Equation 20 holds, where rate choices r_b made at $t = 1$ in counterfactual choices d are optimal given d.

I additionally assume that d_{-b} and rates are exogenous: (a) for all j, $r_{bc}^j = f(z_b, d_b, d_{-b})$ for exogenous characteristics z_b, and (b) that the distribution of (d_{-b}, z_b) conditional on $d_i = d$ does not depend on d. In my setting, (a) involves solving for counterfactual rates given alternate choice d using my rate-setting rule given by the first order conditions at $t = 1$, and (b) is satisfied as this is a simultaneous move game.

$$\sup_d \Pi(d, d_{-b}, r_b) \leq \Pi(d_b, d_{-b}, r_b) \tag{20}$$

This setup implies that for any $d' \in \mathcal{D}_b$, Equation 21 holds.

$$\Pi(d, d_{-b}, r_b) - \Pi(d', d_{-b}, r_b) \equiv \Delta\Pi(d, d', d_{-b}, r_b) \geq 0 \tag{21}$$

Given these assumptions, I proceed to estimate $F(O_b)$, $E(\{m\})$, and $M(\{B_{bm}\})$ in turn, via three steps.

First, I consider a particular inequality implied by this revealed preference argument, by comparing bank profit from the observed choice to a deviation d' by the bank to get

$\Delta\Pi(d, d', d_{-b}, r_b) \geq 0$. For mobile platform adoption, I compare adopting versus not adopting. For branching decisions, I consider deviations based on opening or closing a branch. For market entry decisions, I consider deviations based on entering or not entering a market.

Second, to bring this to the data, I construct an approximation to this inequality based on my parametric profit function specification, $\Delta\hat{\Pi}(d, d', d_{-b}, r_b) \geq 0$. This approximation depends only on the unknown parameters of interest along with observable quantities. In particular, when computing the profit for the deviation, I solve out for the counterfactual rates that banks would optimally set at $t = 1$ given their deviations at $t = 0$, via their first order conditions. I denote banks' $t = 1$ profits by π.

Third, I address the fact that this approximation $\Delta\hat{\Pi}(\cdot)$ induces two types of error relative to the bank's true difference in profit $\Delta\Pi(\cdot)$.

$$\varepsilon_b = \underbrace{\left(\Delta\pi(d, d', d_{-b}, r_b^*) - E[\Delta\pi(d, d', d_{-b}, r_b^*)]\right)}_{\text{Expectational errors}} - \underbrace{\left(\Delta\hat{\pi}(d, d', d_{-b}, r_b, M) - E[\Delta\hat{\pi}(d, d', d_{-b}, r_b, M)]\right)}_{\text{Approximation errors}} \tag{22}$$

$$\xi_b = E[\Delta\pi(d, d', d_{-b}, r_b^*)] - E[\Delta\hat{\pi}(d, d', d_{-b}, r_b, M)] \tag{23}$$

First, there are *approximation errors* ε_b. I construct sample moments from the moment inequalities by taking the sample mean across banks, and I can assume these *approximation errors* have mean 0 given that this is a symmetric information simultaneous game, as detailed in Pakes et al. (2015). Second, there are *structural errors* ξ_b which are differences in profits that are observed by banks but unknown to me as the econometrician. These *structural errors* are not necessarily mean-independent from the banks' choice d and thus cause a selection problem. I overcome this selection problem for each fixed cost function, detailed below.

Branch Maintenance Cost. Branch maintenance costs take the form

$$M(\{B_{bm}\}) = \sum_m (M + \xi_{bm}^B) \cdot B_{bm} \tag{24}$$

The parameter M captures the per-branch maintenance cost, and ξ_b^B is bank b's structural disturbance to this cost in market m.

To estimate branch maintenance costs M, I consider deviations based on banks adding $d + 1$ or subtracting $d - 1$ one branch at random among markets that they have branches in. I choose these deviations so that the inequality given by $d + 1$ provides a lower bound, Equation 25, and the inequality given by $d - 1$ provides an upper bound Equation 26, for branch maintenance costs M.

$$
\begin{aligned}
\text{Adding a branch:} \qquad & \Delta\hat{\Pi}(d, d+1, d_{-b}, r_b) + \varepsilon_b \geq 0 \\
E[(\hat{\pi}(d, d_{-b}, r_b)) - d(M + \xi^B_{bm}) - (\hat{\pi}(d+1, d_{-b}, r_b) - (d+1)(M + \xi^B_{bm}))] & \geq 0 \\
E[\hat{\pi}(d, d_{-b}, r_b) - \hat{\pi}(d+1, d_{-b}, r_b) - d(M + \xi^B_{bm}) + (d+1)(M + \xi^B_{bm}))] & \geq 0 \\
E[\hat{\pi}(d, d_{-b}, r_b) - \hat{\pi}(d+1, d_{-b}, r_b) + (M + \xi^B_{bm}))] & \geq 0 \\
E[\hat{\pi}(d, d_{-b}, r_b) - \hat{\pi}(d+1, d_{-b}, r_b)] + M & \geq 0 \\
\text{Lower Bound for M:} \qquad E[\hat{\pi}(d+1, d_{-b}, r_b) - \hat{\pi}(d, d_{-b}, r_b)] & \leq M
\end{aligned} \tag{25}
$$

$$
\begin{aligned}
\text{Subtracting a branch:} \qquad & \Delta\hat{\Pi}(d, d-1, d_{-b}, r_b) + \varepsilon_b \geq 0 \\
E[(\hat{\pi}(d, d_{-b}, r_b)) - d(M + \xi^B_{bm}) - (\hat{\pi}(d-1, d_{-b}, r_b) - (d-1)(M + \xi^B_{bm}))] & \geq 0 \\
E[\hat{\pi}(d, d_{-b}, r_b) - \hat{\pi}(d-1, d_{-b}, r_b) - d(M + \xi^B_{bm}) + (d-1)(M + \xi^B_{bm}))] & \geq 0 \\
E[\hat{\pi}(d, d_{-b}, r_b) - \hat{\pi}(d-1, d_{-b}, r_b) - (M + \xi^B_{bm}))] & \geq 0 \\
E[\hat{\pi}(d, d_{-b}, r_b) - \hat{\pi}(d-1, d_{-b}, r_b)] - M & \geq 0 \\
\text{Upper Bound for M:} \qquad E[\hat{\pi}(d, d_{-b}, r_b) - \hat{\pi}(d-1, d_{-b}, r_b)] & \geq M
\end{aligned} \tag{26}
$$

The ordered nature of this choice problem is beneficial as it implies that the structural errors are differenced out, as discussed in Ishii (2004) and Pakes et al. (2015), under certain reasonable symmetry assumptions. In the derivation above I use that the unconditional expectations $\mathbb{E}_b[\varepsilon_b] = \mathbb{E}_b[\xi^M_b] = 0$. I construct sample analogs of these population moments in Equations 27 and 28 to use in estimation.

$$
\frac{1}{|\mathcal{B}|} \sum_b [\hat{\pi}(d+1, d_{-b}, r_b) - \hat{\pi}(d, d_{-b}, r_b)] \leq M \tag{27}
$$

$$
\frac{1}{|\mathcal{B}|} \sum_b [\hat{\pi}(d, d_{-b}, r_b) - \hat{\pi}(d-1, d_{-b}, r_b)] \geq M \tag{28}
$$

Note that by choosing branches among markets where banks already have branches induces a truncation problem in my estimation. I address this via a symmetry assumption for ξ^B_{bm}.

Market Entry Cost. Market entry costs are given by

$$
E(\{m\}) = \sum_m (E \cdot D_{bm} + \xi^E_{bm}) \cdot \text{Non-Local}_m \tag{29}
$$

I parameterize market entry costs to be a function of the distance between bank b's headquarter m_b^{HQ} and the new market m, denoted D_{bm}, where the parameter E captures the entry cost per unit of distance. Non-Local$_m$ is an indicator variable tracking whether market m is non-local to the bank, so that it has to pay an entry cost in order to originate loans to customers within it. ξ_{bm}^E is bank b's structural disturbance to this cost in market m.

To estimate market entry costs E, I consider deviations based on banks entering d_+ or leaving d_- a market, each at random, as in Equations 30 and 31.

$$\begin{aligned}
\text{Entering a Market:} \qquad & \Delta\hat{\Pi}(d, d_+, d_{-b}, r_b) + \varepsilon_b \geq 0 \\
E\big[(\hat{\pi}(d, d_{-b}, r_b)) - \sum_m (E \cdot D_{bm} + \xi_{bm}^E) \cdot \text{Non-Local}_m & \\
-(\hat{\pi}(d_+, d_{-b}, r_b) - \sum_{m+1} (E \cdot D_{bm} + \xi_{bm}^E) \cdot \text{Non-Local}_m)\big] \geq 0 & \\
E\big[\hat{\pi}(d, d_{-b}, r_b) - \hat{\pi}(d_+, d_{-b}, r_b) & \\
-\sum_m (E \cdot D_{bm} + \xi_{bm}^E) \cdot \text{Non-Local}_m + \sum_{m+1} (E \cdot D_{bm} + \xi_{bm}^E) \cdot \text{Non-Local}_m)\big] \geq 0 & \\
E\big[\hat{\pi}(d, d_{-b}, r_b) - \hat{\pi}(d_+, d_{-b}, r_b) + (E \cdot D_{bm'} + \xi_{bm'}^E) \cdot \text{Non-Local}_{m'})\big] \geq 0 & \\
E\big[\hat{\pi}(d, d_{-b}, r_b) - \hat{\pi}(d_+, d_{-b}, r_b)\big] + E \cdot D_{bm'} \geq 0 & \\
\text{Lower Bound for E:} \qquad \frac{E\big[\hat{\pi}(d_+, d_{-b}, r_b) - \hat{\pi}(d, d_{-b}, r_b)\big]}{D_{bm'}} \leq E &
\end{aligned} \tag{30}$$

$$\begin{aligned}
\text{Exiting a Market:} \qquad & \Delta\hat{\Pi}(d, d_-, d_{-b}, r_b) + \varepsilon_b \geq 0 \\
E\big[(\hat{\pi}(d, d_{-b}, r_b)) - \sum_m (E \cdot D_{bm} + \xi_{bm}^E) \cdot \text{Non-Local}_m & \\
-(\hat{\pi}(d_-, d_{-b}, r_b) - \sum_{m-1} (E \cdot D_{bm} + \xi_{bm}^E) \cdot \text{Non-Local}_m)\big] \geq 0 & \\
E\big[\hat{\pi}(d, d_{-b}, r_b) - \hat{\pi}(d_-, d_{-b}, r_b) & \\
-\sum_m (E \cdot D_{bm} + \xi_{bm}^E) \cdot \text{Non-Local}_m + \sum_{m-1} (E \cdot D_{bm} + \xi_{bm}^E) \cdot \text{Non-Local}_m)\big] \geq 0 & \\
E\big[\hat{\pi}(d, d_{-b}, r_b) - \hat{\pi}(d_-, d_{-b}, r_b) - (E \cdot D_{bm'} + \xi_{bm'}^E) \cdot \text{Non-Local}_{m'})\big] \geq 0 & \\
E\big[\hat{\pi}(d, d_{-b}, r_b) - \hat{\pi}(d_-, d_{-b}, r_b)\big] - M \geq 0 & \\
\text{Upper Bound for E:} \qquad \frac{E\big[\hat{\pi}(d, d_{-b}, r_b) - \hat{\pi}(d_-, d_{-b}, r_b)\big]}{D_{bm'}} \geq E &
\end{aligned} \tag{31}$$

Note that ξ_{bm}^E may be unobservably high for a bank b that is entering a new market which is Non-Local$_m$, and unobservably low for a bank b that is exiting a market that is Non-Local$_m$. Thus, the structural error ξ_{bm}^E need not be mean-independent of Non-Local$_m$. In the derivation above, I assume that conditional on the distance of the market to bank b's headquarters, $D_{bm'}$, ξ^E_{bm} is mean independent of Non-Local$_m$, which is a selection on observables assumption.

I construct sample analogs of these population moments in Equations 32 and 33 to use in estimation.

$$\frac{1}{|\mathcal{B}|}\sum_b \frac{[\hat{\pi}(d_+, d_{-b}, r_b) - \hat{\pi}(d, d_{-b}, r_b)]}{D_{bm'}} \leq E \tag{32}$$

$$\frac{1}{|\mathcal{B}|}\sum_b \frac{[\hat{\pi}(d, d_{-b}, r_b) - \hat{\pi}(d_-, d_{-b}, r_b)]}{D_{bm'}} \geq E \tag{33}$$

Adoption Cost. Adoption costs take the form

$$F(O_b) = (F + \xi^O_b) \cdot O_b \tag{34}$$

The parameter F captures digital platform adoption costs, where O_b is an indicator variable tracking whether bank b has a digital platform. ξ^O_b is bank b's structural disturbance to digital platform adoption costs.

To estimate fixed adoption cost of mobile platforms F, I construct inequalities based on adopting versus not adopting, as in Equations 35 and 36, where ε_b is the approximation error and ξ^O_b is the structural error. The revealed preference of adopters gives me an upper bound for the cost F, while the revealed preference of non-adopters gives me a lower bound for F.

$$\begin{aligned} \Delta\hat{\Pi}(1, 0, d_{-b}, r_b) + \varepsilon_b \geq 0 \quad \text{if } O^*_b = 1 \\ E[\Delta\hat{\pi}(1, d_{-b}, r_b) - F - \xi^O_b - \Delta\hat{\pi}(0, d_{-b}, r_b)|O^*_b = 1] \geq 0 \\ E[\Delta\hat{\pi}(1, d_{-b}, r_b) - \Delta\hat{\pi}(0, d_{-b}, r_b)|O^*_b = 1] - E[\xi^O_b|O^*_b = 1] \geq F \end{aligned} \tag{35}$$

$$\begin{aligned} \Delta\hat{\Pi}(0, 1, d_{-b}, r_b) + \varepsilon_b \geq 0 \quad \text{if } O^*_b = 0 \\ E[\Delta\hat{\pi}(0, d_{-b}, r_b) - (\Delta\hat{\pi}(1, d_{-b}, r_b) - F - \xi^O_b)|O^*_b = 0] \geq 0 \\ E[\Delta\hat{\pi}(1, d_{-b}, r_b) - \Delta\hat{\pi}(0, d_{-b}, r_b)|O^*_b = 0] - E[\xi^O_b|O^*_b = 0] \leq F \end{aligned} \tag{36}$$

If I could additionally claim that $\mathbb{E}[\xi^O_b|O^*_b = 1] = 0$ and $\mathbb{E}[\xi^O_b|O^*_b = 0] = 0$, then the moment inequalities in Equations 35 and 36 could be used for estimation. However, this structural error term is observed by the bank at the time of adopting mobile technology and thus we expect that it has larger mean for $O_b = 1$ than for $O_b = 0$. I overcome this selection problem by constructing instruments. Suppose that I have two positive bank-level variables Z^+_b and

Z_b^- such that Equations 37 and 38 hold.

$$\mathbb{E}[Z_b^+ \cdot \xi_b^O | O_b = 1] = 0 \tag{37}$$
$$\mathbb{E}[Z_b^- \cdot \xi_b^O | O_b = 0] = 0 \tag{38}$$

I interact these instruments with the moment inequalities to obtain, via the exogeneity restrictions in Equations 37 and 38, along with the mean-zero assumption for approximation error, the resulting moment inequalities in Equations 41 and 42. I can estimate these via method of moments. For my instruments, I let $Z_b^+ = 1$ if a bank has above median AT&T coverage, and 0 otherwise. Similarly, I let $Z_b^- = 1$ when $Z_b^+ = 0$.

$$E[Z_b^+(\Delta\hat{\pi}(1, d_{-b}, r_b) - \Delta\hat{\pi}(0, d_{-b}, r_b))|O_b^* = 1] \geq F \tag{39}$$
$$E[Z_b^-(\Delta\hat{\pi}(1, d_{-b}, r_b) - \Delta\hat{\pi}(0, d_{-b}, r_b))|O_b^* = 0] \leq F \tag{40}$$

I construct sample analogs of these population moments,

$$\frac{1}{|\mathcal{B}|}\sum_b [Z_b^+(\Delta\hat{\pi}(1, d_{-b}, r_b) - \Delta\hat{\pi}(0, d_{-b}, r_b))|O_b^* = 1] \geq F \tag{41}$$
$$\frac{1}{|\mathcal{B}|}\sum_b [Z_b^-(\Delta\hat{\pi}(1, d_{-b}, r_b) - \Delta\hat{\pi}(0, d_{-b}, r_b))|O_b^* = 0] \leq F \tag{42}$$

C. Counterfactuals

C.1. Investment Restrictions and Computation Details

While in principle there may be many different counterfactual equilibria in the absence of digital platforms, I aim to study one that is close to the observed economy. To this end, I put two restrictions on banks' investment decisions. First, I assume that banks are endowed with their *local markets*, which are the markets that they operate branches in at the beginning of the period, and can choose to scale up or down the number of branches that they have in these counties. I restrict banks' branching decisions along this dimension due to the empirical evidence presented in Section IV, which documents that digital platform adoption does not lead to large changes in the local markets in which banks operate a non-zero number of branches. Additionally, this assumption simplifies the setting and reduces the number of possible multiple equilibria. Further, I bound banks branches by their investments prior to the development of digital platforms, in 2008. Bank branches have been falling in aggregate since the development of digital platforms, and the intuition of this restriction is to isolate the share of banks' branch closures during this period that occurred due to this technology.

Second, I allow banks to exit markets in the counterfactual equilibrium in the absence of digital platforms, but do not allow banks to enter markets in which they were not already providing services. As shown in Section IV, banks have been entering new markets during this period, and the intuition here is again to capture the share of new markets that banks entered directly due to digital platform technology.

I additionally adjust the utility of the outside option in the counterfactual equilibrium to account for the fact that non-banks mortgage lenders during this period have also acquired digital platform technologies which provide direct demand benefits and allow these non-banks to provide mortgages at lower costs, which they may pass through. Specifically, I scale down the utility of the outside option by assuming that all non-banks de-digitize, and charge rates that are 20% higher relative to the mean rates in the sample.

In the counterfactual equilibria, at $t = 0$ banks observe their *local markets*, and optimize by making investment decisions.[40] Due to the computational burden of enumerating all potential equilibria, I follow Lee and Pakes (2009) and Wollmann (2018) by considering a learning process for equilibrium selection. The counterfactual computation assumes an ordering of banks' decisions based on banks' pre-existing number of branches. The bank with the most branches best-responds, assuming that all other banks continue to play their equilibrium strategy. The bank with the second-most branches then best-responds, but replaces the strategy of the first bank with its new best response. This process iterates through all banks until a full cycle is completed and no bank wants to deviate, resulting in a simultaneous move Nash equilibrium.

C.2. Expected Consumer Surplus

Consumer surplus is the utility, in dollar terms, that an agent receives in a choice situation. Agents choose the decision that produces the greatest utility, and thus following Train 2009 Chapter 3, the consumer surplus associated with a set of alternatives is,

$$CS = \frac{1}{\alpha} \max_j (U_j) \tag{43}$$

where α is the marginal utility of income, $\alpha = \dfrac{\partial U}{\partial Y}$ for Y the income of the agent.

As the researcher, I cannot observe an agent's utility U_j but only V_j in a decomposition of utility into observable and unobservable components, $U_j = V_j + \varepsilon_j$. Thus, I can calculate

[40] In the estimation exercise, the shape of the distribution of fixed cost structural errors is unrestricted. In computing the counterfactual, I assume that the fixed cost parameters are equal to the midpoint of their upper and lower bounds, and I set the structural errors equal to 0. Alternatively, I could specify a distribution for the structural errors and take draws over this distribution.

expected consumer surplus, where the expectation is taken over values of ε_j,

$$E[CS] = \frac{1}{\alpha} E[\max_j (V_j + \varepsilon_j)] \tag{44}$$

Assuming that these unobservable components ε_j are independently and identically distributed extreme value, it has been shown that this expression becomes

$$E[CS] = \frac{1}{\alpha} \log \left(\sum_{j=0}^{J} \exp(V_j) \right) + C \tag{45}$$

where C is an unknown constant representing the fact that the absolute level of utility cannot be measured, and is irrelevant from a policy perspective. Setting the utility of the outside option to 0 also normalizes $C = 0$. Further, the negative of the price term (or simply the price term in the case of deposit markets) is equal to the marginal utility of income by definition.

For mortgage markets, I calculate expected consumer surplus by averaging bank characteristics across all counties in which a bank operates in the digital and non-digital equilibrium, and then summing across banks $j \in \mathcal{J}$ and the outside option. This effectively calculates consumer surplus for an average national mortgage market, and makes the change in consumer surplus more comparable to that of the deposit markets. If instead I calculate changes in consumer surplus at the county level and sum across counties, there is the additional benefit of bank entry into counties, which pushes up the consumer surplus changes by even more for mortgage markets. In reality, both deposit and mortgage markets are benefiting from entry so that the changes in consumer surplus reported in the paper are likely to be lower bounds.

A.5. Model Robustness

A. Digitalization and Bank Mergers

When I compute the counterfactual equilibria without digital platforms, I do not endogenously allow banks to dissolve the mergers that have occurred during the time period of digital technologies. If the economies of scale related to digitalization induces mergers between banks, evaluating this effect is important in understanding the overall effect that digitalization has on the competitive landscape of the banking sector. I tabulate the mergers that have occurred during 2010-2019 and find that they largely take place among very small banks, and thus are unlikely to affect the results in the baseline quantitative analysis.

A.6. Additional Model Results

A. Alternate Deposit Demands

Table A.27 Simple Version of Deposit Demand

Parameter	j = Insured		j = Uninsured	
Deposit Rate	1.575*	(0.804)	2.152***	(0.615)
Digital Platforms	0.203***	(0.055)	0.458***	(0.165)
Branches	0.002	(0.010)	0.182***	(0.044)
Overall Coverage	0.001**	(0.000)	0.001	(0.001)
Lag Assets	0.967***	(0.009)	0.940***	(0.019)
Lag Insured Ratio	1.160***	(0.030)	-5.274***	(0.103)

This table reports the slope estimates from the second stage of a 2SLS regression on measures of bank mortgage applications on digital platform adoption, instrumented via banks' AT&T exposure.

Table A.28 Micro Channels in Deposit Demand

Parameter	j = Insured		j = Uninsured	
Deposit Rate	2.104**	(0.970)	1.962***	(0.483)
Digital Platforms	0.208***	(0.042)	0.349***	(0.128)
Digital Platforms with Widespread Branch Network	-0.145***	(0.041)	0.136	(0.112)
Highly Rated Digital Platforms	0.105***	(0.028)	0.274***	(0.074)
Branches	0.036	(0.029)	0.342***	(0.076)
Lag Loan Losses	-0.627	(0.555)	-6.432***	(1.970)
Lag Assets	0.979***	(0.012)	0.965***	(0.017)
Lag Insured Ratio	1.154***	(0.033)	-5.234***	(0.095)
Local Population	-0.000	(0.000)	-0.000***	(0.000)

This table reports the slope estimates from the second stage of a 2SLS regression on measures of bank mortgage applications on digital platform adoption, instrumented via banks' AT&T exposure.