Essays in Banking and Consumer Finance

Charlotte Haendler

Boston College - March 27, 2023

A dissertation

submitted to the Faculty of

the department of Finance

in partial fulfillment

of the requirements for the degree of

Doctor of Philosophy

Essays in Banking and Consumer Finance

Charlotte Haendler

Boston College - March 27, 2023

Advisors: Philip E. Strahan (Chair), Edith Hotchkiss, Ronnie Sadka, Rawley Heimer

Abstract

My dissertation consists of two chapters. In the first chapter, I show that the growing trend in financial services digitalization has introduced a new dimension along which commercial banks compete, with consequences for the local economy. Small community banks (SCBs) are slow to implement mobile technologies and lose deposits to larger, better-digitalized banks following mobile infrastructure improvements. This dynamic negatively affects their small business lending, for they have historically relied on information and liquidity synergies with deposits to maintain their competitive advantage in such markets. Larger banks and FinTech firms prove to be imperfect substitutes in this setting, and the local economy benefits less from digitalization in areas where SCBs had an important presence before its advent. The second chapter, co-authored with prof. Rawley Heimer, focuses on the outcomes of consumers' efforts to achieve restitution for disputed financial services. We find that complaints filed with the Consumer Financial Protection Bureau (CFPB) from low-income and Black zip codes are 30% less likely to be resolved with the consumer receiving financial restitution. The gap in financial restitution was scarcely present under the Obama administration, but grew substantially under the Trump administration. We attribute the change in financial restitution under

different political regimes to companies anticipating a more industry-friendly CFPB, as well as to the more industry-friendly leadership of the CFPB achieving less financial restitution for low-income and Black filers. The financial restitution gap cannot be explained by differences in product usage nor the quality of complaints, which we measure using textual analysis.

Keeping Up in the Digital Era:

How Mobile Technology Is Reshaping the Banking Sector*

Charlotte Haendler†
Boston College

Abstract

I show that the growing trend in financial services digitalization has introduced a new dimension along which commercial banks compete. Small community banks (SCBs) are slow to implement mobile technologies and lose deposits to larger, better-digitalized banks following mobile infrastructure improvements. This dynamic negatively affects their small business lending, for they have historically relied on information and liquidity synergies with deposits to maintain their competitive advantage in such markets. Larger banks and FinTech firms prove to be imperfect substitutes in this setting, and the local economy benefits less from digitalization in areas where SCBs had an important presence before its advent.

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

---

*I thank Phil Strahan, Edith Hotchkiss, Rawley Heimer, Ronnie Sadka, Boston College Brownbag attendees, and Green Line Macro Meeting attendees for helpful feedback. I thank Manasa Gopal and Philipp Schnabl for UCC Filings data and helpful comments. H. Doumit provided fantastic Telecom industry insights. Any remaining errors or omissions are the author's responsibility.

†Boston College, Carroll School of Management. Email: haendler@bc.edu.

1 Introduction

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

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

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

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

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

Building on intuition from the two sets of results just presented, I proceed to show that it is indeed (under-digitalized) small community banks that experience significant deposit outflows following improvements in the county's mobile infrastructure. At the same time, it is (better-digitalized) non-community banks that experience large deposit inflows in the county. Further, I show small community banks lower deposit rates and increase fees after the improvements. With their superior technology, larger banks attract those depositors at the margins that the infrastructural improvement turns digital-savvy by raising the opportunity cost of staying with an under-digitalized bank. At a technological disadvantage, small community banks choose to exploit their remaining customers instead. Additionally, these dynamics are associated with a significantly higher likelihood of branch closure for small community banks. Mobile banking is acting as a *de facto* negative technological shock for these institutions.

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

I show small community banks reduce their small business lending substantially once the technology shock hits. A significant improvement in a county's mobile infrastructure results in a 15% decrease in the total amount of small business lending from local small community banks. Further, small community banks with prior high deposit-to-asset ratios are driving this decrease, confirming the deposit channel. Small community banks also reduce the percentage of nonperforming small business loans on their balance sheet. In the meantime, they keep their other lending positions—mortgages, student loans, car loans, and so on—virtually unchanged.

I then proceed to investigate whether other players fill this lending gap. Non-community banks gain deposits after mobile infrastructure upgrades. However, I show they do not increase their small business lending in return. This finding is not entirely surprising, given these institutions are known for their transactional approach and reliance on hard information (Cole et al. (2004), Berger et al. (2005), Uchida et al. (2012)). Within the context of small business lending, deposits do not carry the same information and liquidity advantages for them as they would for small community banks. FinTech firms seem to make up for part of the decrease instead, almost exclusively in metropolitan areas.[1]

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

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

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

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

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

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

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

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

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

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

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

2 Data

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

2.1 Mobile banking data

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

[4] Data.ai website.

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

2.2 Mobile Infrastructure data

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

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

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

- PCS (Personal Communication Service) Broadband: 1850-1990 MHz Band comprising Broadband PCS, Broadband PCS G block 1910-1915 and 1990-1995 MHz Bands Market Area;

- AWS (Advanced Wireless Services): comprising AWS-1 1710-1755 and 2110-2155 MHz Bands, H Block 1915-1920 and 1995-2000 MHz Bands, AWS-3 1695-1710 1755-1780 and 2155-2180 MHz Bands, AWS-4 2000-2020 and 2180-2200 MHz Bands;

- 2.5 GHz: comprised of Broadband Radio Service, Educational Broadcast Radio Service.

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

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

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

[7]FCC License View.

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

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

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

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

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

2.3 Small business lending data

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

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

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

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

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

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

3 Technology-spurred competition on deposits

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

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

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

where $outcome\ variable_{b,c,t}$ is either the logarithm of deposits or the deposit pricing of bank b in county c and year t. $Spectrum\ expansions_{c,t-1}$ capture mobile infrastructure improvements in county c and year $t-1$ in terms of 100s of MHz of new electromagnetic spectrum allotted to mobile network operators, and $app\ available_{b,t-1}$ is a dummy variable equal to 1 if bank b has an app on either Google Play or the Apple Store in year $t-1$. α_c represent county fixed effects, α_t are year fixed effects, and $X_{c,t-1}$ is a set of lagged county-year controls that include the number of bank b branches, population, GDP, income per capita, employment rate, and number of businesses. This specification focuses on the differential effect of having an app at the time of the infrastructural improvement. Being able to provide mobile banking services should become relatively more valuable after the improvement, given the customer's opportunity cost of staying with a bank that does not provide these services increases as they improve and become more popular.

First, Panel A of Table 3 reports estimation results for the above specification with the logarithm of deposits as the dependent variable. It shows only banks that provide mobile banking services at the time of the infrastructural improvements experience deposit growth (positive and significant interaction of $spectrum\ expansions_{t-1}$ with $app\ available_{t-1}$). At a higher competitive disadvantage after the improvements, banks without an app lose significant amounts of deposits instead (negative coefficient on $spectrum\ expansions_{t-1}$). Overall, some depositors seem to prefer better-digitalized banks after local mobile infrastructure improvements. A significant increase in $sp.\ expansions_{c,t-1}$ of 100MHz—like the one that happened for many counties between 2015 and 2017—results in a 7.71% increase in deposits for banks that provide a mobile banking app (column 3).

Panel B of Table 3 presents results on deposit pricing. The analysis is again run at the year-county-bank level but with deposit rates derived from FDIC Call Reports data at the bank-year level due to a lack of access to more detailed branch-level data. Therefore, it is assumed that a bank applies the same deposit rate across all the counties it operates in. In particular, total bank interest expenses over total bank deposits is the dependent variable in columns 1 to 3, and total bank interest expenses net of service fees over total bank deposits is the dependent variable in columns 4 to 6. According to one of the predictions of Jiang et al. (2022)'s model of banking competition under digital disruption, banks that do not digitalize raise prices on their customers. Notwithstanding the approximate measurement of the deposit rates, the analysis seems to empirically support the model. Banks without an app lower their deposit rates and increase their service fees after local mobile infrastructure improvements (negative and significant coefficient on *sp. expansions*$_{c,t-1}$ in columns 1 and 4). On the other hand, better-digitalized banks try to appeal even more to customers by lowering their pricing (*app available*$_{b,t-1}$ $\times$ *sp. expansions*$_{c,t-1}$ always positive and statistically significant across specifications). Columns 2-3 and 5-6 introduce county x year fixed effects, controlling for changes in local demand. Results remain consistent.

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

4 Mobile technology adoption

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

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

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

A third element could be the type of bank making the decision. Larger banks have a clear advantage in the upfront investment required to adopt and maintain mobile banking technologies. Banks with broader geographical coverage might have an incentive for early adoption because they are susceptible to a larger number of competitors and mobile infrastructure of varying quality. Banks relying on in-person interactions with their customers might not see the need for this kind of technology in their operations instead. Therefore, I set up a framework that considers banks across the three main dimensions of size, geographical coverage, and scope of operations. I categorize depository institutions with total assets below $1 billion as *small community banks*. These banks are small and known to be highly reliant on the soft information they gather through repeated interactions with their customers. Building on FDIC (2012), I then categorize as *big community banks* depository institutions that satisfy the following conditions: (i) total assets above $ 1 billion, (ii) loans to assets $> 33\%$, (iii) deposits to assets $> 50\%$, (iv) 75 branches at most, (v) number of large metropolitan statistical areas with branches < 3,[12] (vi) number of states with branches < 4, and (vii) no branches with more than $ 5 billion in deposits. This category captures institutions that did embrace some economies of scale but kept within the boundaries and the modus operand of the community bank business model.[13] All other depository institutions enter the residual category of *non-community banks*. These institutions are mainly banks with regional or national coverage, known to be highly reliant on hard information in their decision-making and to maintain a transactional approach with their customers.

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

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

I then investigate the weight that each of these elements—customer base, mobile infrastructure quality, bank type—carry in the decision to adopt mobile technology. Table 4, Panel A, presents hazard ratios from a parametric hazard model run across all banks, where the end event is the adoption of the app.[14] In other words, the model captures whether each of the different elements above results in quicker or slower app adoption. Hazard ratios above 1 represent quicker app adoption, and hazard ratios below 1 represent slower app adoption. Therefore, estimates show an older customer base slows down app adoption, whereas a highly educated one speeds it up.[15] Further, big community banks and non-community banks are much faster than small community banks in adopting mobile banking technology.[16] Interestingly, mobile infrastructure improvements, a deposit-weighted average of $\textit{spectrum expansions}_{c,t}$ across the counties the institution operates in, seem to slow adoption down.

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

$$\begin{aligned}\%\ \textit{branches providing app}_{c,t} &= \alpha_s + \alpha_t + \beta_1\ \textit{spectrum expansions}_{c,t-1} + \\ &\beta_2\ \textit{county demographics}_c + \beta_3\ \textit{county banking characteristics}_{c,t} + \epsilon_{c,t}, \quad (2)\end{aligned}$$

where the dependent variable $\%\ \textit{branches providing app}_{c,t}$ is the number of county c year t branches belonging to banks that provide a mobile banking app over total county c year t branches. Among the independent variables, $\textit{spectrum expansions}_{c,t-1}$ capture mobile

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

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

[16]Non-community banks appear to be slower than big community banks in the model because it excludes banks that already have an app at the start of the sample.

infrastructure improvements in county c and year $t-1$ in terms of 100s of MHz of new electromagnetic spectrum allotted to mobile network operators. $County\ demographics_c$ include share of population ages 65 and older and share of population that received higher education as per the 2010 Census. $County\ banking\ characteristics_{c,t}$ include $I(big\ comm.\ bank\ branches_{c,t})$ and $I(non\text{-}comm.\ bank\ branches_{c,t})$, dummies for the presence of at least one big community bank branch in county c at year t and the presence of at least one non-community bank branch, respectively. This specification includes state fixed effects and year fixed effects.

In Panel B of Table 4, column 1 shows a one-standard-deviation increase in the share of population 65 and older in the county (5.18%) reduces the % branches providing an app in the county by 5.8% with respect to the unconditional sample mean (53.12%). At the same time, a-one-standard-deviation increase in the share of highly educated population (7.31%) increases the % branches providing an app in the county by 6.90% with respect to the unconditional sample mean. Interestingly, $spectrum\ expansions_{c,t-1}$ continue to play a deterring role in app adoption. In column 2, I add $I(big\ comm.\ bank\ branches_{c,t})$ and $I(non\text{-}comm.\ bank\ branches_{c,t})$ to the specification. The addition raises the within-R-square from 4.76% to 10.1%. Both the presence of big community banks and non-community banks branches carry positive and significant coefficients. Having a big community bank in the county raises the percentage of branches that provide mobile banking apps in the county by 8.45% with respect to the unconditional sample mean. Having a non-community bank in the county raises the percentage of branches that provide mobile banking apps by 23.74% with respect to the unconditional sample mean. Columns 3 and 4 repeat the analysis with the percentage of deposits held at banks that provide apps as dependent variable instead. Patterns are similar. Local spectrum expansions are again confirmed to carry a negative weight in app adoption.

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

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

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

Overall, the analysis reveals that bank type is an important determinant of timely app adoption. In particular, all tests point to small community banks being the slowest adopters. Furthermore, during the manual collection of banking apps' launch dates, I got the sense that even if available, small community banks' apps generally offer fewer services and updates with respect to larger banks' apps.[17] Because bank type is an important determinant of app adoption, arguably unrelated to mobile infrastructure improvements and capturing

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

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

5 Consequences for small community banks

Considering Section 3 and Section 4 together, results would suggest that it might be small community banks that lose deposits to larger, better-digitalized banks following mobile infrastructure improvements. In order to investigate whether this is the case, in Table 5 I re-run equation 1 and compare the original estimates (columns 1 and 3) with additional ones where I substitute $\textit{app available}_{b,t-1}$ with $\textit{bank type}_{b,t}$ (columns 2 and 4). Columns 1 and 2 of Panel A show that it is indeed small community banks that lose deposits to larger, better-digitalized banks following mobile infrastructure improvements. In particular, the coefficient on $\textit{sp. expansions}_{c,t-1}$ remains virtually unchanged across the two specifications. Further, columns 3 and 4 confirm that results with $\textit{bank type}_{b,t}$ still mirror results with $\textit{app available}_{b,t-1}$ under the inclusion of county x year and bank fixed effects. Under the new specification, a significant increase in $\textit{sp. expansions}_{c,t-1}$ of 100MHz—like the one that happened for many counties between 2015 and 2017—results in a 10.4% increase in non-community bank deposits (column 4). Interestingly, big community banks do not seem to be subject to the same issues small community banks suffer from when it comes to mobile banking services. *Big community bank*$_{b,t}$ displays a positive and significant coefficient across specifications, greater in absolute magnitude than the one of *sp. expansions*$_{c,t-1}$ in column 2. Panel B repeats the exercise with deposit rates as the outcome variable. Estimates further confirm that it is small community banks that lower their deposit rates after local mobile infrastructure improvements (negative and significant coefficient on *sp. expansions*$_{c,t-1}$, virtually identical across columns 1 and 2).

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

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

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

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

where *lending amount*$_{b,t}$ is the amount of small business/real estate/individual/other lending on the balance sheet of SCB b in year t. The source of these lending data are FDIC Call Reports at the institution level, with small business lending being reliably proxied by Commercial and Industrial Loans below $1 million (FDIC (2020b)). To allow for my county-level mobile infrastructure improvement measure (*sp. expansions*$_{c,t-1}$) and further local economic controls, I link these institution-level data to the county c the small community bank b has most of its deposits in in year t. Because more than 90% of SCBs have most of their deposits in one county, the measurement error should be minimal. Then, α_b represent bank fixed effects, α_t are year fixed effects, α_c are county fixed effects, and $X_{c,t-1}$ is a set of lagged county-year demographic and end economic controls that include the number of branches, population, GDP, income per capita, employment rate, and the number of small businesses.[18]

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

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

approximatively a 9% decrease in the small business lending reported on the balance sheet of active SCBs.

In Panel B of Table 6, I show that the more reliant a small community bank is on deposits, the more it decreases its small business lending once the technology shock hits. To do so, I employ the following specification:

$$\begin{aligned} ln(lending\ amount_{c,b,t}) = \alpha_c + \alpha_b + \alpha_t + \beta_1\ spectrum\ expansions_{c,t-1} \\ + \beta_2\ avg_{[t-2,t-4]}\left(\frac{deposits_b}{assets_b}\right) + \beta_3\ avg_{[t-2,t-4]}\left(\frac{deposits_b}{assets_b}\right) \\ *\ spectrum\ expansions_{c,t-1} + \gamma X_{c,t-1} + \alpha_c + \epsilon_{c,b,t}, \quad (4) \end{aligned}$$

which captures reliance on deposits through the average of bank deposits over assets across the previous three years. Under this new specification, the coefficient on $spectrum\ expansions_{c,t-1}$ becomes insignificant, whereas the interaction coefficient β_3 is the one that is negative and significant (column 1, just above the 10% significance threshold). This dynamic confirms the decline in small business lending highlighted in the previous panel is a consequence of the deposit outflows triggered by the mobile technology shock. These outflows hurt banks that highly depend on deposits the most and cause them to decrease their small business lending. Furthermore, the interaction of $spectrum\ expansions_{c,t-1}$ with a bank characteristic allows me to better control for local demand by introducing county x year fixed effects (column 2). Results increase in magnitude and significance under these stronger controls.

In light of these findings, I further investigate whether SCBs become warier in providing credit to risky small businesses. Such a move could be related to the market becoming more opaque for them under the informational loss that accompanies deposit outflows. To test this possibility, in Panel C of Table 6, I re-employ equation 3. However, the dependent variables are now the share of nonaccrual commercial and industrial loans (column 1), the share of still-accruing commercial and industrial loans at least 30 days past due (column 2), and the share of commercial and industrial loans charge-offs (column 3). I show all three present decreasing patterns after improvements in the local mobile infrastructure.[19] A significant increase in $sp.\ expansions_{c,t-1}$ of 100MHz—like the one that happened for many counties between 2015 and 2017—results in approximately a 34.57% (29.54%, 18.72%) decrease in the share of nonaccrual (still-accruing 30 days past due, charge-offs) commercial and industrial loans with respect to the unconditional sample mean of 1.64% (1.31%, 0.55%). Coefficient significance is high in the first two columns, and slightly lower for charge-offs in column 3. Overall, evidence suggests SCBs are shifting towards safer small business loans after local mobile infrastructure improvements.

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

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

$$at\ least\ one\ net\ closing\ (opening)_{c,t} = \alpha_c + \alpha_t + \beta_1\ spectrum\ expansions_{c,t-1} + \gamma X_{c,t-1} + \epsilon_{c,t}, \tag{5}$$

where $at\ least\ one\ net\ closing(opening)_{c,t}$ is a dummy variable equal to 1 if county c has witnessed at least one net SCB branch closing (opening) in year t (i.e., if the number of SCB branches in county c and year t is smaller (larger) than the number the previous year), and $spectrum\ expansions_{c,t-1}$ capture mobile infrastructure improvements in county c and

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

year $t-1$ in terms of 100s of MHz of new electromagnetic spectrum allotted to mobile network operators. α_c represent county fixed effects, α_t are year fixed effects, and $X_{c,t-1}$ is a set of lagged county-year demographic and end economic controls that include the number of branches, population, GDP, income per capita, employment rate, and the number of businesses.

Table 7 shows improvements in the local mobile infrastructure significantly increase the likelihood of SCB net branch closures and significantly decrease the likelihood of SCB net branch openings. According to columns 1 and 3, a significant increase in $sp.\ expansions_{c,t-1}$ of 100MHz—like the one that happened for many counties between 2015 and 2017—results in a 39.53% increase (50.75% decrease) in the likelihood of witnessing at least one a SCB net branch closure (opening) the year after with respect to the sample mean of 0.1475 (0.0938). In columns 2 and 4, I substitute $spectrum\ expansions_{c,t-1}$ with $sp.\ exp.\ above\ Ymedian_{c,t-1}$, a dummy variable equal to 1 if spectrum expansions by MNOs in county c are above the yearly median for the country in year $t-1$. This substitution captures the difference made by being on the greater side of mobile infrastructure improvements and ensures outliers do not drive the results in these county-level regressions. Simply being above the country median for mobile infrastructure improvements increases (decreases) the likelihood of witnessing at least one SCB net branch closure (opening) by 14.58% (25.05%). These magnitudes are very high, especially when considering that around 60% of SCBs have less than four branches total.[20] This mobile technology shock is threatening the survival of existing SCBs and discouraging their future development.

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

6 Consequences for small businesses

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

6.1 Small business lending decrease

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

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

where $scb\,SBLs_{c,t}$ is the sum of the number/amount of all commercial and industrial loans below \$1 million on the balance sheets of SCBs having county c as their main county of operation in year t (Call Report data), and $spectrum\; expansions_{c,t-1}$ capture mobile infrastructure improvements in county c and year $t-1$ in terms of 100s of MHz of new electromagnetic spectrum allotted to mobile network operators. α_c represent county fixed effects, α_t are year fixed effects, and $X_{c,t-1}$ is a set of lagged county-year demographic and end economic controls that include the number of small community banks branches, population, GDP, income per capita, employment rate, and the number of small businesses.

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

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

I use Community Reinvestment Act (henceforth CRA) data for this part of the analysis. Up to this point, I have used Call Report data on commercial and industrial loans below \$1 million to analyze small business lending. However, Call Report data are only available at the institution level, and I cannot geographically link them to the mobile infrastructure data with sufficient precision in the case of bigger banks. CRA reports are mandatory for banks with assets above the pre-determined \$1.1 billion/\$1.2 billion threshold. Hence, they cover all the non-community banks in my sample and $\sim 75\%$ of the big community banks. For each of these banks, they detail small business loan originations by borrowers' location, which I can then link to the mobile infrastructure data. Therefore, I use the total amount of locally originated CRA small business loans to borrowers in the county as the left-hand-side variable in a year-county-level specification similar to equation 6 above. According to estimates in Table 9, despite receiving deposit inflows after local mobile infrastructure improvements, bigger banks do not seem to increase their small business lending in return. Neither big community banks nor non-community banks respond to mobile infrastructure improvements in their small business lending.

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

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

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

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

6.2 Real effects

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

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

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

This specification aims to gauge real effects of the decrease in small business lending by SCBs after local mobile infrastructure improvements (section 6.1). The coefficient of interest is β_2, the interaction between the share of SCB deposits in the county at the start of the sample and local mobile infrastructure improvements.[21] It captures whether real consequences of mobile infrastructure improvements differ where SCBs had an important presence before the mobile technology shock. In particular, I would expect a negative and significant β_2 coefficient if FinTech firms are not fully able to substitute away the decrease in small business lending by SCBs.

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

Looking at the interaction coefficient alone (β_2 in equation 6 above), column 1 in Panel A shows how a significant improvement in mobile infrastructure—100 MHz—translates to a 0.3% decrease in employment by small businesses with 1 to 19 employees if small community banks served half of the depositors in the county in 2010 (the sample average prior to the mobile technology shock and financial services digitalization).[22] Column 1

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

[22] 1*0.5*(-0.00593) = 0.003.

in Panel B shows how a significant improvement in mobile infrastructure translates to a 0.26% decrease in wages for such businesses under the same condition.[23] Column 1 in Panel C shows how a significant improvement in mobile infrastructure translates to an 0.18% decrease in the number of such businesses under the same condition.[24] These effects are then counteracting positive and mostly significant coefficients on $spectrum\ expansions_{c,t-1}$, whereby an important improvement in mobile infrastructure translates to a 0.24%, 0.56%, and 0.23% increase in employees, wages, and the number of businesses, respectively, for businesses with fewer than 20 employees. Nonetheless, they suggest that the economic growth that mobile infrastructure improvements would help achieve is partly neutralized by a lack of funding by SCBs following the same improvements. Magnitudes appear generally small, but note unconditional sample averages are 0.23%, 2.27%, and -0.14% for employees, wages, and businesses' growth, respectively, for businesses with less than 20 employees. Moreover, nearly half of the counties had SCBs covering more than 50% of overall deposits in 2010, prior to digitalization. Similar patterns with slightly larger magnitudes appear in column 2 across panels regarding businesses with 20 to 49 employees. In contrast, larger businesses with 50 to 499 employees do not appear to respond to mobile infrastructure improvements.

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

[23] 1*0.5*(-0.00522) = 0.0026.

[24] 1*0.5*(-0.00358) = 0.0018.

7 Robustness

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

7.1 Geographical distribution of effects

One primary concern in the analysis is the geographical distribution of the highlighted effects. SCBs have a weaker presence in urban areas, where cell phone reception might also be better. Therefore, I might be picking up urban versus rural evolutionary patterns rather than the effect of mobile technology adoption. Against this argument, my measure of mobile infrastructure improvements does not present significant differences across rural and urban geographies (see Figure 1 for reference). However, it captures the ex-ante intention to use more electromagnetic spectrum for smoother mobile communications with no guarantee of the actual implementation. For such reasons, in Appendix B, I replicate the analysis within three different subsamples: counties belonging to metropolitan statistical areas, counties belonging to micropolitan statistical areas, and the remaining counties (which I label rural).[25]

Table B.1 replicates bank competition estimates: Panel A on deposit flows, Panel B on deposit pricing. Results across subsamples (columns 2 to 4) are consistent with the full-sample estimates reported in column 1 and previously presented in the paper. The only difference is the lack of significance and a smaller magnitude of $spectrum\ expansion_{c,t-1}$ regarding county deposits in micropolitan areas, suggesting less to no outflows from SCBs in

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

such counties. As much in metropolitan areas as in rural ones, there however appear to be significant outflows of deposits from SCBs following improvements in local mobile infrastructure. Furthermore, SCBs exploit their remaining customers through higher pricing, whereas bigger, better-digitalized banks increase their rates to appeal to potential new customers.

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

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

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

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

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

7.2 Event study analysis

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

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

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

where $\textit{at least one net closing}_{\,c,t}$ is a dummy variable equal to 1 if county c has witnessed at least one net SCB branch closing in year t, $Treated_c$ is a dummy variable equal to 1 if the county witnessed a year-on-year percentage increase of at least 60% and to 0 if it belongs to the control group, $Post_t$ is a dummy variable equal to 1 for the treated and their matched controls in the two years after the event, and α_k represent cohort fixed effects (one for each pair of treated county with its control).[26] Table C.1 reports estimates of this regression. The coefficient of interest β_1 is positive and significant across specifications, meaning higher rates of SCB branch closures in treated counties after the event ($\sim +30\%$ increase with respect to the unconditional sample average). Figure C.1 reports changes in interaction coefficients over the event years with respect to the year prior the event. The parallel trends assumption seems satisfied, and the year after the event presents the only positive coefficient significantly different from zero, for treated counties alone. Even in this setting, SCB branch closures appear to be negatively affected by mobile infrastructure improvements.

Second, I test whether SCBs decrease their small business lending following important im-

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

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

7.3 Instrumental variable analysis

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

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

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

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

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

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

8 Conclusion

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

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

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

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

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

References

Agarwal, S., Hauswald, R., 2010. Distance and private information in lending. The Review of Financial Studies 23, 2757–2788.

Andersen, T. B., Bentzen, J., Dalgaard, C.-J., Selaya, P., 2012. Lightning, it diffusion, and economic growth across us states. Review of Economics and Statistics 94, 903–924.

Berg, T., Fuster, A., Puri, M., 2021. Fintech lending. Annual Review of Financial Economics 14.

Berger, A. N., Miller, N. H., Petersen, M. A., Rajan, R. G., Stein, J. C., 2005. Does function follow organizational form? evidence from the lending practices of large and small banks. Journal of Financial economics 76, 237–269.

Berger, A. N., Udell, G. F., 1994. Lines of credit and relationship lending in small firm finance. Jerome Levy Economics Institute Working Paper .

Berger, A. N., Udell, G. F., 2002. Small business credit availability and relationship lending: The importance of bank organisational structure. The economic journal 112, F32–F53.

Bonfim, D., Nogueira, G., Ongena, S., 2021. "sorry, we're closed" bank branch closures, loan pricing, and information asymmetries. Review of Finance 25, 1211–1259.

Bongini, P., Di Battista, M. L., Zavarrone, E., 2007. The value of relationship lending: small banks in an era of consolidation. Economic Notes 36, 209–230.

Boot, A., Hoffmann, P., Laeven, L., Ratnovski, L., 2021. Fintech: what's old, what's new? Journal of financial stability 53, 100836.

Brown, J. R., Cookson, J. A., Heimer, R. Z., 2019. Growing up without finance. Journal of Financial Economics 134, 591–616.

Buchak, G., Matvos, G., Piskorski, T., Seru, A., 2018. Fintech, regulatory arbitrage, and the rise of shadow banks. Journal of Financial Economics 130, 453–483.

Carter, D. A., McNulty, J. E., 2005. Deregulation, technological change, and the business-lending performance of large and small banks. Journal of Banking & Finance 29, 1113–1130.

Carter, D. A., McNulty, J. E., Verbrugge, J. A., 2004. Do small banks have an advantage in lending? an examination of risk-adjusted yields on business loans at large and small banks. Journal of Financial Services Research 25, 233–252.

Cole, R. A., Goldberg, L. G., White, L. J., 2004. Cookie cutter vs. character: The micro structure of small business lending by large and small banks. Journal of financial and quantitative analysis 39, 227–251.

Dante, H., Makridis, C., 2021. The rise of mobile banking and the displacement of brick-and-mortar branches, 2014-2019. Available at SSRN 3822561 .

DeYoung, R., Hunter, W. C., Udell, G. F., 2004. The past, present, and probable future for community banks. Journal of Financial Services Research 25, 85–133.

Drechsler, I., Savov, A., Schnabl, P., 2017. The deposits channel of monetary policy. The Quarterly Journal of Economics 132, 1819–1876.

Drechsler, I., Savov, A., Schnabl, P., 2021. Banking on deposits: Maturity transformation without interest rate risk. The Journal of Finance 76, 1091–1143.

Erel, I., Liebersohn, J., 2020. Does fintech substitute for banks? evidence from the paycheck protection program. Tech. rep., National Bureau of Economic Research.

FDIC, 2012. Community banking study 2012 .

FDIC, 2020a. Community banking study 2020 .

FDIC, 2020b. Report no. 2020-04, measurement of small business lending using call reports: Further insights from the small business lending survey .

Fuster, A., Plosser, M., Schnabl, P., Vickery, J., 2019. The role of technology in mortgage lending. The Review of Financial Studies 32, 1854–1899.

Gopal, M., Schnabl, P., 2020. The rise of finance companies and fintech lenders in small business lending. NYU Stern School of Business .

Guriev, S., Melnikov, N., Zhuravskaya, E., 2021. 3g internet and confidence in government. The Quarterly Journal of Economics 136, 2533–2613.

Ho, C. S. T., Berggren, B., 2020. The effect of bank branch closures on new firm formation: the swedish case. The Annals of Regional Science 65, 319–350.

Hughes, J. P., Jagtiani, J., Mester, L. J., 2016. Is bigger necessarily better in community banking? Federal Reserve Bank of Cleveland Working Paper .

Hughes, J. P., Jagtiani, J., Mester, L. J., Moon, C.-G., 2019. Does scale matter in community bank performance? evidence obtained by applying several new measures of performance. Journal of Banking & Finance 106, 471–499.

Jiang, E. X., Yu, G. Y., Zhang, J., 2022. Bank competition amid digital disruption: Implications for financial inclusion .

Li, L., Loutskina, E., Strahan, P. E., 2019. Deposit market power, funding stability and long-term credit. Tech. rep., National Bureau of Economic Research.

Manacorda, M., Tesei, A., 2020. Liberation technology: Mobile phones and political mobilization in africa. Econometrica 88, 533–567.

Mester, L. J., Nakamura, L. I., Renault, M., 2007. Transactions accounts and loan monitoring. The Review of Financial Studies 20, 529–556.

Nguyen, H.-L. Q., 2019. Are credit markets still local? evidence from bank branch closings. American Economic Journal: Applied Economics 11, 1–32.

Nguyen, N. T., Barth, J. R., 2020. Community banks vs. non-community banks: Where is the advantage in local small business funding? Atlantic Economic Journal 48, 161–174.

Norden, L., Weber, M., 2010. Credit line usage, checking account activity, and default risk of bank borrowers. The Review of Financial Studies 23, 3665–3699.

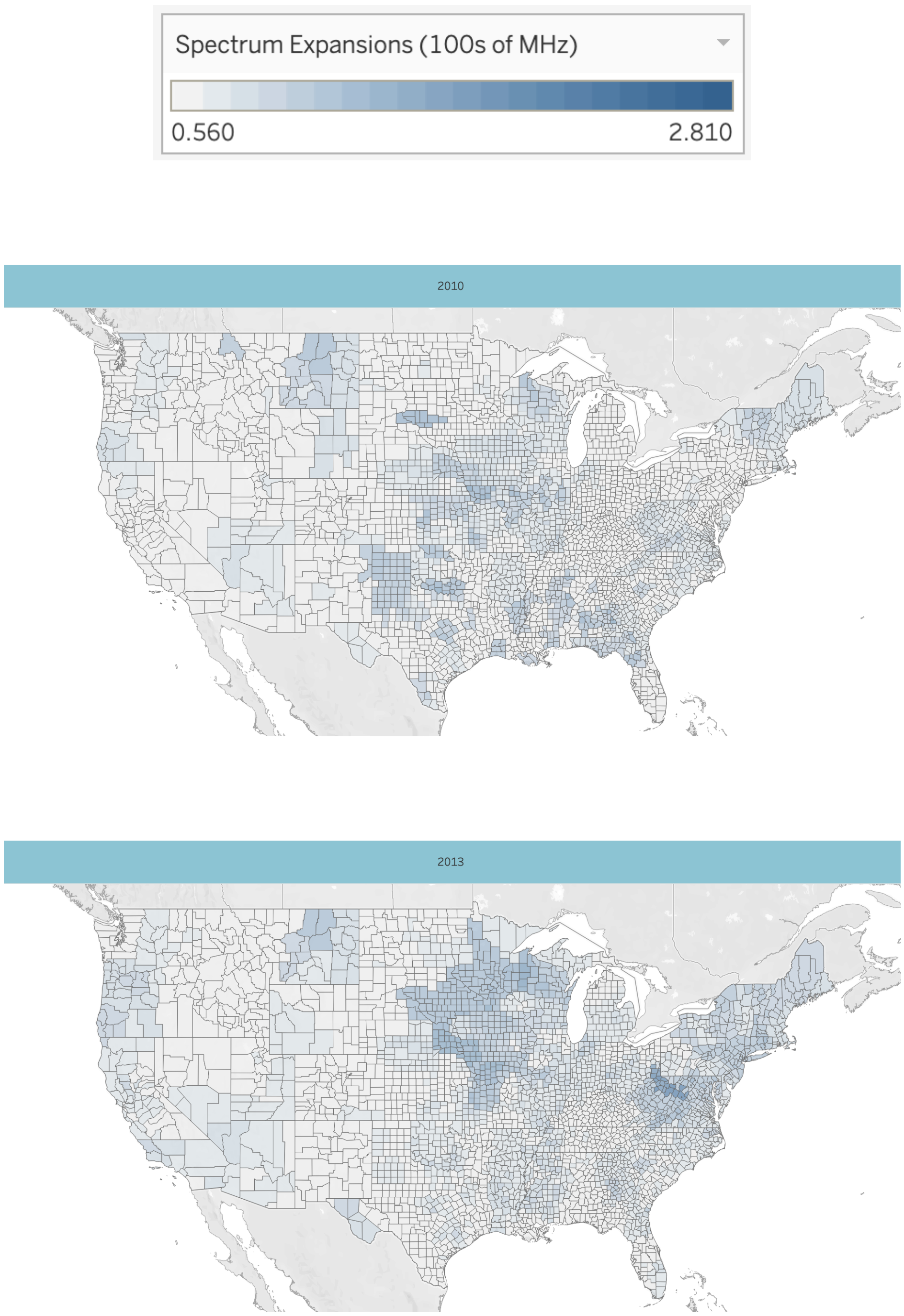
Petersen, M. A., Rajan, R. G., 1994. The benefits of lending relationships: Evidence from small business data. The journal of finance 49, 3–37.

Uchida, H., Udell, G. F., Yamori, N., 2012. Loan officers and relationship lending to smes. Journal of Financial Intermediation 21, 97–122.

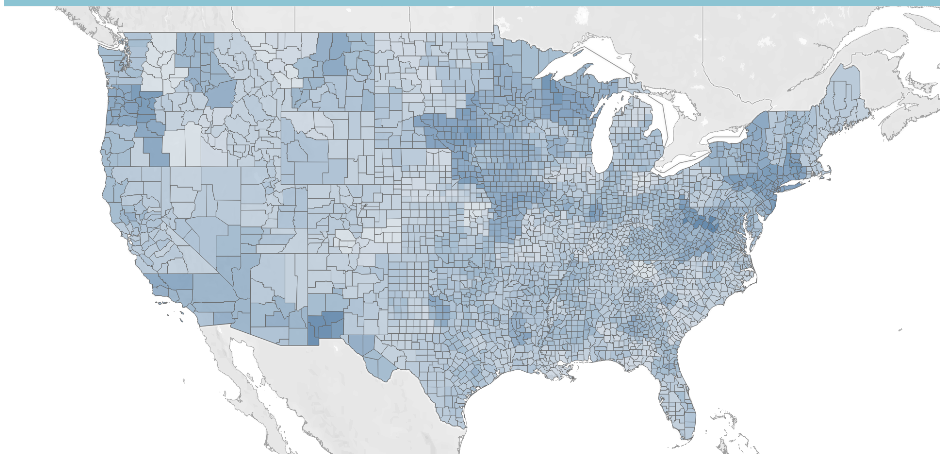
Yang, J., 2021. Deposit-lending synergies: Evidence from chinese students at us universities. Journal of Financial and Quantitative Analysis pp. 1–27.

Figure 1: **Spectrum holdings over time**

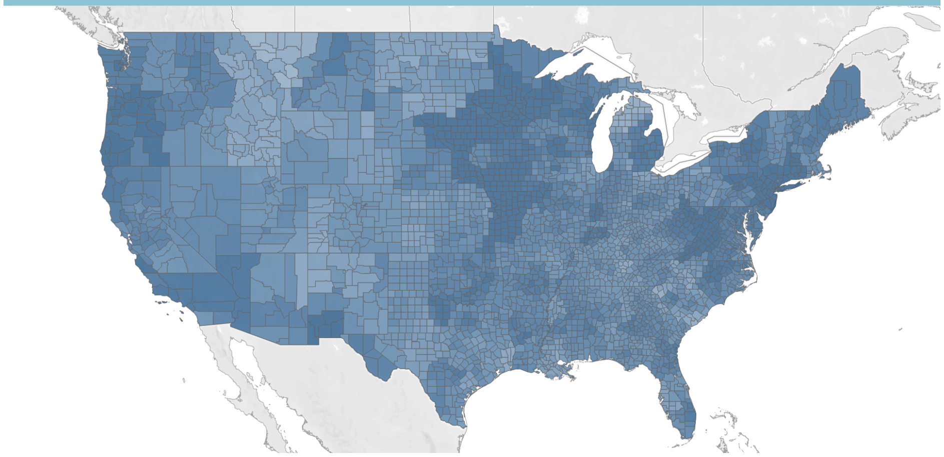
Description: This figure maps Mobile Network Operators' spectrum expansion across U.S. counties by year.



2015



2017



2019

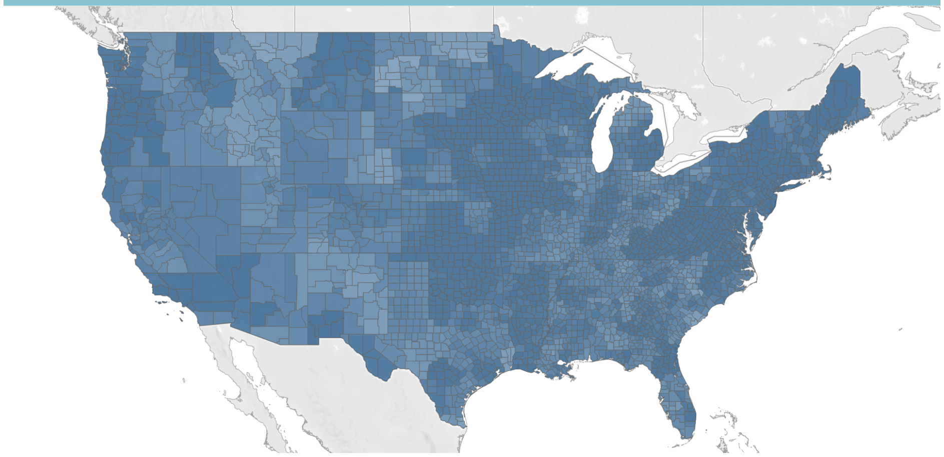


Figure 2: **Mobile banking adoption rates over time**

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

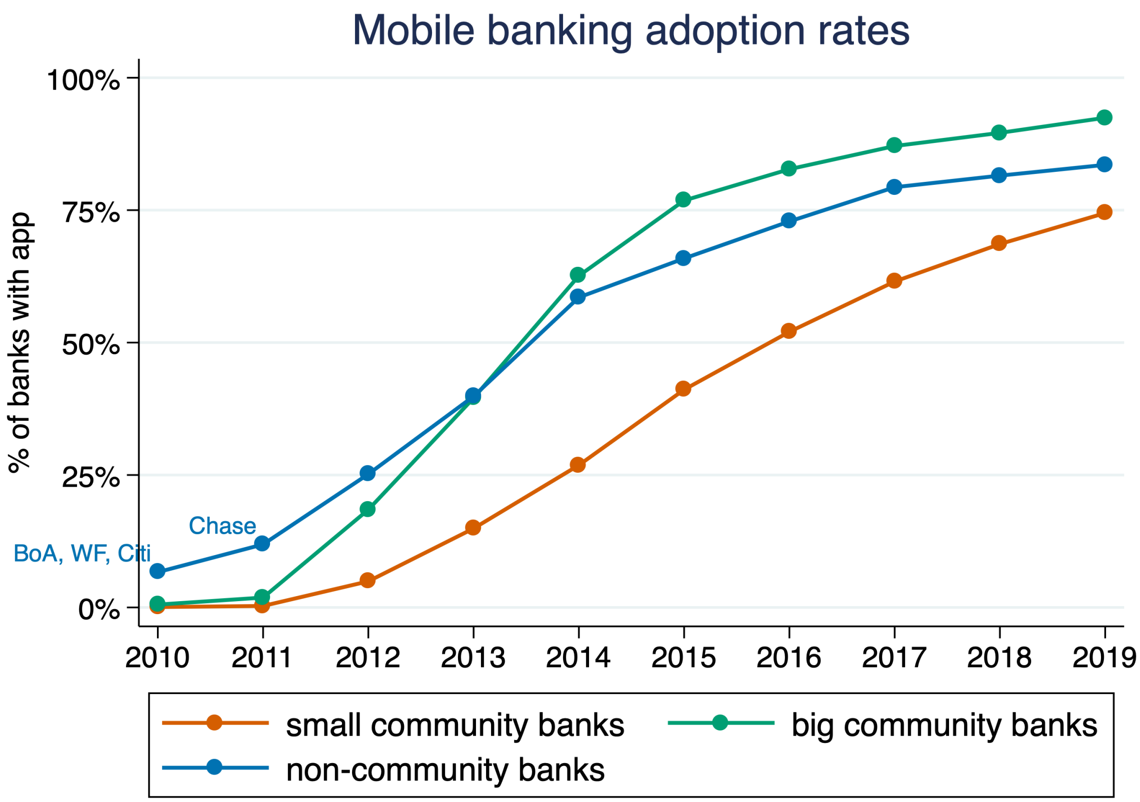


Table 1: **Spectrum Expansions (in 100s of MHz)**

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

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

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

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

	# institutions	avg. # branches	avg. deposits	avg. # branches per county	avg. deposits per county	avg. # of counties
June 2010						
community banks	6,277	4.04	USD 157 mill.	2.08	USD 89 mill.	1.98
big community banks	557	18.54	USD 1.12 bill.	4.37	USD 336 mill.	5.38
non-community banks	240	230.02	USD 22.48 bill.	3.81	USD 2.11 bill.	42.49
full sample	7,153	12.95	USD 991 mill.	2.32	USD 177 mill.	3.60
June 2019						
community banks	4,442	4.34	USD 210 mill.	1.99	USD 107 mill.	2.29
big community banks	556	19.59	USD 1.72 bill.	3.93	USD 468 mill.	6.37
non-community banks	304	184.91	USD 35.8 bill.	3.21	USD 4.31 bill.	40.78
full sample	5,351	16.29	USD 2.41 bill.	2.26	USD 386 mill.	4.89

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

Description: This table presents results on technology-driven competition on deposits. The dependent variable is the natural logarithm of bank b deposits in county c and year t in Panel A, deposit interest rates (total interest expenses over total deposits) of bank b in county c and year t in columns 1 to 3 of Panel B, net deposit interest rates (total interest expenses net of service fees over total deposits) of bank b in county c and year t in columns 4 to 6 of Panel B. Across specifications, $sp.\ expansions_{\,c,t-1}$ captures MNOs spectrum expansions in county c and year $t-1$ and $app\ available_{\,b,t-1}$ is a dummy equal to 1 if bank b offers a banking app in year $t-1$. Standard errors are clustered at county level; ***, **, * denote 1%, 5%, and 10% statistical significance; - denotes a coefficient absorbed by fixed effects..

Panel A: Deposit Flows

	ln(deposits $_{b,c,t}$)		
	(1)	(2)	(3)
sp. expansions $_{c,t-1}$	-0.0276*	-	-
	(0.016)		
app available $_{b,t-1}$	-0.0209	-0.0178	-0.123***
	(0.041)	(0.044)	(0.010)
app available $_{b,t-1}$ × sp. exp. $_{c,t-1}$	0.0990***	0.105***	0.0725***
	(0.015)	(0.017)	(0.0077)
# branches $_{b,c,t-1}$	0.0929***	0.0926***	0.0771***
	(0.015)	(0.015)	(0.014)
ln(population $_{c,t-1}$)	0.791***	-	-
	(0.11)		
ln(# businesses $_{c,t-1}$)	0.179***	-	-
	(0.068)		
employment rate $_{c,t-1}$	0.506***	-	-
	(0.15)		
ln(personal income pc $_{c,t-1}$)	0.281***	-	-
	(0.044)		
ln(county GDP $_{c,t-1}$)	0.0702***	-	-
	(0.022)		
county FE	x		
year FE	x		
county x year FE		x	x
bank FE			x
observations	222,212	220,936	220,784
R-squared	0.409	0.415	0.689

Panel B: Deposit Pricing

	interest paid % $_{b,c,t}$			net interest paid % $_{b,c,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
sp. expansions $_{c,t-1}$	-0.0376***	-	-	-0.177***	-	-
	(0.0028)			(0.0090)		
app available $_{b,t-1}$	-0.152***	-0.155***	-0.0871***	-0.553***	-0.589***	-0.193***
	(0.0020)	(0.0022)	(0.0013)	(0.0067)	(0.0074)	(0.0024)
app available $_{b,t-1}$ × sp. exp. $_{c,t-1}$	0.0582***	0.0594***	0.0327***	0.215***	0.234***	0.0789***
	(0.0014)	(0.0016)	(0.00089)	(0.0046)	(0.0052)	(0.0016)
# county branches $_{b,c,t-1}$	-0.00199***	-0.00196***	-0.0000732**	-0.000779***	-0.000634***	-0.000113*
	(0.000061)	(0.000063)	(0.000036)	(0.00020)	(0.00021)	(0.000066)
ln(population $_{c,t-1}$)	0.0229	-	-	0.175**	-	-
	(0.025)			(0.081)		
ln(GDP $_{c,t-1}$)	-0.0423***	-	-	-0.0614***	-	-
	(0.0065)			(0.021)		
ln(personal income pc $_{c,t-1}$)	0.0360***	-	-	0.0295	-	-
	(0.013)			(0.041)		
ln(# businesses $_{c,t-1}$)	0.154***	-	-	0.112*	-	-
	(0.018)			(0.058)		
employment rate $_{c,t-1}$	-0.114***	-	-	-0.0510	-	-
	(0.042)			(0.14)		
county FE	x			x		
year FE	x			x		
county x year FE		x	x		x	x
bank FE			x			x
observations	223,535	222,261	222,111	223,535	222,261	222,111
R-squared	0.463	0.491	0.877	0.171	0.186	0.942

Table 4: **App adoption**

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

Panel A: Hazard model

	app available$_{b,t}$
	(1)
big community bank$_{b,t-1}$	2.3077***
	(0.1173)
non-community bank$_{b,t-1}$	1.4622***
	(0.1122)
deposit-weighted avg sp. expansions$_{b,t-1}$	0.3246***
	(0.0121)
deposit-weighted avg % of pop. 65y and older$_{b,t-1}$	0.8340***
	(0.0311)
deposit-weighted avg % of pop. w/higher education$_{b,t-1}$	1.1559***
	(0.0258)
observations	39,951

Panel B: Linear regression models

	% branches providing app$_{c,t}$		% deposits with app$_{c,t}$	
	(1)	(2)	(3)	(4)
sp. expansions$_{c,t-1}$	-0.0298***	-0.0269***	-0.0254***	-0.0225**
	(0.0090)	(0.0085)	(0.0097)	(0.0092)
% pop. 65y and older$_{c,2010}$	-0.595***	-0.321***	-0.666***	-0.386***
	(0.057)	(0.054)	(0.061)	(0.058)
% pop. w/higher education$_{c,2010}$	0.501***	0.346***	0.578***	0.419***
	(0.036)	(0.035)	(0.044)	(0.042)
I(big comm. bank branches$_{c,t}$)		0.0449***		0.0461***
		(0.0049)		(0.0053)
I(non-comm. bank branches$_{c,t}$)		0.126***		0.128***
		(0.0083)		(0.0088)
state FE	x	x	x	x
year FE	x	x	x	x
observations	31,612	31,612	31,612	31,612
R-squared	0.644	0.664	0.610	0.630
Within R2	0.0476	0.101	0.0518	0.0991

Panel C: app adoption and spectrum expansions

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

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

Description: This table compares results on technology-driven competition on deposit when considering *app available* $_{b,t-1}$ as a proxy for mobile technology adoption and quality (columns 1 and 3 across panels) and when considering *bank type* (*small community banks*, *big community banks*, *non-community banks*) as a proxy for mobile technology adoption and quality (columns 2 and 4 across panels). The dependent variable is the natural logarithm of bank b deposits in county c and year t in Panel A, deposit interest rate (total interest expenses over total deposits) of bank b (which operates in county c) in year t in Panel B. Across specifications, *sp. expansions* $_{c,t-1}$ captures MNOs spectrum expansions in county c and year $t-1$. Standard errors are clustered at county level; ***, **, * denote 1%, 5%, and 10% statistical significance; - denotes a coefficient absorbed by fixed effects.

Panel A: Deposit Flows

	ln(deposits $_{b,c,t}$)			
	(1)	(2)	(3)	(4)
sp. expansions $_{c,t-1}$	-0.0276*	-0.0273**	-	-
	(0.016)	(0.014)		
app available $_{b,t-1}$	-0.0209		-0.123***	
	(0.041)		(0.010)	
app available $_{b,t-1}$ × sp. exp. $_{c,t-1}$	0.0990***		0.0725***	
	(0.015)		(0.0077)	
big community bank $_{b,t}$		0.382***		0.0386*
		(0.038)		(0.023)
non-community bank $_{b,t}$		0.143***		-0.166***
		(0.049)		(0.030)
big community bank $_{b,t}$ × sp. exp. $_{c,t-1}$		0.0254*		0.0225**
		(0.014)		(0.0097)
non-community bank $_{b,t}$ × sp. exp. $_{c,t-1}$		0.123***		0.104***
		(0.011)		(0.0085)
# branches $_{b,c,t-1}$	0.0929***	0.0905***	0.0771***	0.0771***
	(0.015)	(0.015)	(0.014)	(0.014)
ln(population $_{c,t-1}$)	0.791***	0.519***	-	-
	(0.11)	(0.11)		
ln(# businesses $_{c,t-1}$)	0.179***	0.159**	-	-
	(0.068)	(0.066)		
employment rate $_{c,t-1}$	0.506***	0.358**	-	-
	(0.15)	(0.15)		
ln(personal income pc $_{c,t-1}$)	0.281***	0.201***	-	-
	(0.044)	(0.044)		
ln(county GDP $_{c,t-1}$)	0.0702***	0.0858***	-	-
	(0.022)	(0.022)		
county FE	x	x		
year FE	x	x		
county x year FE			x	x
bank FE			x	x
observations	222,212	222,212	220,784	220,784
R-squared	0.409	0.418	0.689	0.689

Panel B: Deposit Pricing

	interest paid % $_{b,c,t}$			
	(1)	(2)	(3)	(4)
sp. expansions $_{c,t-1}$	-0.0376***	-0.0378***	-	-
	(0.0028)	(0.0027)		
app available $_{b,t-1}$	-0.152***		-0.0871***	
	(0.0020)		(0.0013)	
app available $_{b,t-1}$ $\times$ sp. exp. $_{c,t-1}$	0.0582***		0.0327***	
	(0.0014)		(0.00089)	
big comm. bank (BCB) $_{b,t}$		-0.0552***		-0.0112***
		(0.0028)		(0.0026)
non-comm. bank (NCB) $_{b,t}$		-0.192***		-0.137***
		(0.0019)		(0.0030)
BCB $_{b,t}$ $\times$ sp. exp. $_{c,t-1}$		0.0239***		0.0164***
		(0.0018)		(0.0011)
NCB $_{b,t}$ $\times$ sp. exp. $_{c,t-1}$		0.0767***		0.0909***
		(0.0012)		(0.00076)
# county branches $_{b,c,t-1}$	-0.00199***	-0.00155***	-0.0000732**	-0.0000499
	(0.000061)	(0.000061)	(0.000036)	(0.000035)
ln(population $_{c,t-1}$)	0.0229	-0.0429*	-	-
	(0.025)	(0.025)		
ln(GDP $_{c,t-1}$)	-0.0423***	-0.0383***	-	-
	(0.0065)	(0.0064)		
ln(personal income pc $_{c,t-1}$)	0.0360***	-0.000849	-	-
	(0.013)	(0.012)		
ln(# businesses $_{c,t-1}$)	0.154***	0.147***	-	-
	(0.018)	(0.018)		
employment rate $_{c,t-1}$	-0.114***	-0.153***	-	-
	(0.042)	(0.042)		
county FE	x	x		
year FE	x	x		
county x year FE			x	x
bank FE			x	x
observations	223,535	223,535	222,111	222,111
R-squared	0.463	0.475	0.877	0.884

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

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

Panel A: Lending

	ln(C&I loans < 1 mill. $_{b,c,t}$)	ln(real estate loans $_{b,c,t}$)	ln(individual loans $_{b,c,t}$)	ln(other loans $_{b,c,t}$)
	(1)	(2)	(3)	(4)
sp. expansions $_{c,t-1}$	-0.0878**	0.00526	0.000962	0.00631
	(0.037)	(0.0093)	(0.023)	(0.024)
# branches $_{b,c,t-1}$	0.0682***	0.0916***	0.0765***	0.130***
	(0.0077)	(0.0077)	(0.0077)	(0.015)
ln(population $_{c,t-1}$)	-2.959***	0.553***	0.127	0.630
	(0.47)	(0.084)	(0.10)	(0.45)
ln(GDP $_{c,t-1}$)	0.181**	0.0100	0.133***	0.0623
	(0.083)	(0.017)	(0.027)	(0.053)
ln(personal income pc $_{c,t-1}$)	-0.0714	0.0778	0.112	-0.0953
	(0.18)	(0.066)	(0.070)	(0.11)
ln(# small businesses$_{c,t-1}$)	0.649**	0.535***	-0.0244	-0.0649
	(0.25)	(0.069)	(0.077)	(0.21)
employment rate$_{c,t-1}$	-1.092***	-0.226***	0.139	0.854***
	(0.41)	(0.079)	(0.15)	(0.24)
county FE	x	x	x	x
year FE	x	x	x	x
bank FE	x	x	x	x
observations	48,917	48,917	48,917	48,917
R-squared	0.786	0.964	0.910	0.905

Panel B: Small Business Lending, Deposit Channel

	ln(C&I loans < 1 mill. $_{b,t}$)	
	(1)	(2)
sp. expansions$_{c,t-1}$	0.160	-
	(0.17)	
[avg$_{[t-2,t-4]}$(deposit % of assets)]$_{b,t-1}$	-0.291	0.405
	(0.20)	(0.35)
sp. expansions$_{c,t-1}$ $\times$ [avg$_{[t-2,t-4]}$(deposit % of assets)]$_{b,t-1}$	-0.278^{+}	-0.590***
	(0.17)	(0.21)
# branches$_{b,c,t-1}$	0.0687***	0.0678***
	(0.0073)	(0.0090)
ln(population$_{c,t-1}$)	-3.110***	-
	(0.49)	
ln(GDP$_{c,t-1}$)	0.166**	-
	(0.083)	
ln(personal income pc$_{c,t-1}$)	-0.0320	-
	(0.17)	
ln(# small businesses$_{c,t-1}$)	0.700***	-
	(0.27)	
employment rate$_{c,t-1}$	-1.055***	-
	(0.39)	
county FE	x	
year FE	x	
county x year FE		x
bank FE	x	x
observations	46,301	37,325
R-squared	0.763	0.855

Panel C: Small Business Loans Risk

	nonaccrual C&I loans $\%_{b,c,t}$	C&I loans accr. past due $\%_{b,c,t}$	C&I loans charge-offs $\%_{b,c,t}$
	(1)	(2)	(3)
sp. expansions$_{c,t-1}$	-0.567***	-0.381***	-0.103*
	(0.084)	(0.11)	(0.052)
# branches$_{b,c,t-1}$	0.106***	0.125***	0.0350**
	(0.022)	(0.021)	(0.015)
ln(population$_{c,t-1}$)	-1.623**	-0.830	-1.382**
	(0.76)	(0.97)	(0.61)
ln(GDP$_{c,t-1}$)	-0.386	0.384**	0.0441
	(0.31)	(0.18)	(0.12)
ln(personal income pc$_{c,t-1}$)	-1.226**	-0.831**	-0.241
	(0.55)	(0.40)	(0.22)
ln(# small businesses$_{c,t-1}$)	1.403**	0.503	0.258
	(0.70)	(0.69)	(0.51)
employment rate$_{c,t-1}$	-5.306***	-2.726**	0.181
	(0.81)	(1.29)	(0.69)
county FE	x	x	x
year FE	x	x	x
bank FE	x	x	x
observations	47,464	47,464	47,467
R-squared	0.386	0.265	0.211

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

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

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

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

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

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

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

Description: This table presents results on the effect of the mobile technology shock on small business lending by the big community banks and non-community banks filing CRA reports. The dependent variables are the natural logarithm of the amount of local CRA loans originated in county c and year t by big community banks (columns 1 and 2) and by non-community banks (columns 3 and 4). *sp. expansion* $_{c,t-1}$ (columns 1 and 3) captures MNOs spectrum expansion in county c and year $t-1$. *sp. exp. above* $Y - median$ $_{c,t-1}$ (columns 2 and 4) is a dummy variable equal to 1 if *sp. expansion* $_{c,t-1}$ is above the yearly median for the entire country for county c in year $t-1$. Standard errors are clustered at county level; ***, **, * denote 1%, 5%, and 10% statistical significance.

	ln(amount CRA SBLs $_{c,t}$)			
	big community banks		non-community banks	
	(1)	(2)	(3)	(4)
sp. expansion $_{c,t-1}$	-0.0302		-0.0385	
	(0.055)		(0.038)	
sp. exp. above Y-median $_{c,t-1}$		-0.0118		0.0136
		(0.022)		(0.015)
# branches $_{c,t-1}$	0.0281***	0.0281***	0.00187***	0.00184***
	(0.0069)	(0.0069)	(0.00047)	(0.00046)
ln(population $_{c,t-1}$)	0.562	0.578	1.667***	1.681***
	(0.53)	(0.53)	(0.39)	(0.39)
employment rate $_{c,t-1}$	0.625	0.607	-0.916*	-0.935*
	(0.61)	(0.61)	(0.49)	(0.49)
ln(# small businesses $_{c,t-1}$)	0.633**	0.630**	0.234	0.231
	(0.31)	(0.31)	(0.26)	(0.26)
ln(county GDP $_{c,t-1}$)	0.0242	0.0236	0.102	0.0984
	(0.092)	(0.092)	(0.068)	(0.068)
county FE	x	x	x	x
year FE	x	x	x	x
observations	12,717	12,715	22,267	22,242
R-squared	0.851	0.851	0.918	0.917

Table 10: **The Role of Fintech**

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

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

Table 11: **Real Effects**

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

Panel A: Employment Growth

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

Panel B: Wage Growth

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

Panel C: Economic Growth

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

Appendices to:

Keeping up in digital era: a traditional bank perspective.

(intended for online publication)

A Variable Descriptions

Name	Explanation
ln(deposits$_{c,t}$)	Natural logarithm of deposits in county c and year t. *Source: FDIC Summary of Deposits.*
ln(deposits$_{b,c,t}$)	Natural logarithm of bank b deposits in county c and year t. *Source: FDIC Summary of Deposits.*
sp. expansions$_{c,t}$	Additional spectrum allotted to Mobile Network Operators in county c and year t since 2010 (hundreds of MHz). *Source: based on Federal Communication Commission Licenses.*
app available$_{b,t}$	Takes value of 1 if bank b provides mobile banking services in year t. *Source: hand-collected from data.ai.*
# branches$_{c,t}$	Number of branches of bank b in county c and year t. *Source: FDIC Summary of Deposits.*
ln(population$_{c,t}$)	Natural logarithm of county c population in year t. *Source: Census Bureau.*
ln(# businesses$_{c,t}$)	Natural logarithm of county c # of businesses in year t. *Source: Census County Business Patterns.*
employment rate$_{c,t}$	employment rate [0,1] of county c in year t. *Source: Bureau of Labor Statistics.*
ln(personal income pc$_{c,t}$)	Natural logarithm of personal income per capita in county c and year t. *Source: Bureau of Economic Analysis.*
ln(county GDP$_{c,t}$)	Natural logarithm of county c GDP in year t. *Source: Bureau of Economic Analysis.*
big community bank$_{b,t}$	Takes the value of 1 if bank b is a *big community bank* in year t. *Source: bank type framework (Section 4).*
non-community bank$_{b,t}$	Takes the value of 1 if bank b is a *non-community bank* in year t. *Source: bank type framework (Section 4).*
deposit-weighted avg sp. expansions$_{b,t}$	deposit-weighted average of *sp. expansions*$_{c,t}$ across the counties bank b operates in. *Source: based on FCC Licenses & FDIC Summary of Deposits.*
deposit-weighted % pop. 65y and older$_{b,t}$	deposit-weighted average of the percentage [0,1] of population 65-year and older across the counties bank b operates in in year t. *Source: based on Census 2010 & FDIC Summary of Deposits.*
dep.-w. avg % of pop. w/higher ed.$_{b,t}$	deposit-weighted average of the percentage [0,1] of population with higher education across the counties bank b operates in in year t. *Source: based on Census 2010 & FDIC Summary of Deposits.*
% branches providing app$_{c,t}$	percentage [0,1] of county c branches belonging to banks that provide mobile banking services in year t. *Source: based on DIC Summary of Deposits & hand-collected from data.ai.*
% deposits with app$_{c,t}$	percentage [0,1] of county c deposits belonging to banks that provide mobile banking services in year t. *Source: based on DIC Summary of Deposits & hand-collected from data.ai.*
% population 65y and older$_{c,2010}$	percentage [0,1] of population 65-year and older in county c in 2010. *Source: Census 2010.*

Name	Description
% population w/higher education$_{c,2010}$	percentage [0,1] of population with higher education in county c in 2010. *Source: Census 2010.*
I(big comm. bank branches$_{c,t}$)	Takes the value of 1 if there is at least one branch belonging to a *big community bank* in county c and year t. *Source: FDIC Summary of Deposits & bank type framework (Section 4).*
I(non-comm. bank branches$_{c,t}$)	Takes the value of 1 if there is at least one branch belonging to a *non-community bank* in county c and year t. *Source: FDIC Summary of Deposits & bank type framework (Section 4).*
interest paid %$_{b,c,t}$	(total interest expenses / total deposits)*100 for bank b in year t - bank b having a branch in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits.*
net interest paid %$_{b,c,t}$	((total interest expenses - total fees) / total deposits)*100 for bank b in year t - bank b having a branch in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits.*
ln(C&I loans $<$ 1 mill.$_{b,c,t}$)	Natural logarithm of the total amount of commercial and industrial loans below 1 million on the balance sheet of bank b in year t - bank b conducting the majority of its business in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits.*
ln(real estate loans$_{b,c,t}$)	Natural logarithm of the total amount of real estate loans on the balance sheet of bank b in year t - bank b conducting the majority of its business in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits.*
ln(individual loans$_{b,c,t}$)	Natural logarithm of the total amount of individual loans (car loans, student loans, etc.) on the balance sheet of bank b in year t - bank b conducting the majority of its business in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits.*
ln(other loans$_{b,c,t}$)	Natural logarithm of the total amount of individual loans (loans to other institutions, farm loans, etc.) on the balance sheet of bank b in year t - bank b conducting the majority of its business in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits.*
ln(# small businesses$_{c,t}$)	Natural logarithm of county c # of businesses with less than 50 employees in year t. *Source: Census County Business Patterns.*
nonaccrual C&I loans %$_{b,c,t}$	(nonaccrual C&I loans / total C&I loans)*100 for bank b in year t - bank b conducting the majority of its business in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits.*
C&I loans accr. past due %$_{b,c,t}$	(C&I loans still accruing but past due/ total C&I loans)*100 for bank b in year t - bank b conducting the majority of its business in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits.*
C&I loans charge-offs %$_{b,c,t}$	(C&I loans charge-offs/ total C&I loans)*100 for bank b in year t - bank b conducting the majority of its business in county c at time t. *Source: FFIEC Call Reports & FDIC Summary of Deposits.*
at least one net closing$_{c,t}$	Takes the value of 1 if the number of small community bank branches in county c and year t is smaller than the number of small community bank branches in county c and year $t-1$. *Source: FDIC Summary of Deposits.*

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

B Geographical distribution of effects

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

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

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

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

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

Panel A: Deposit Flows

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

Panel B: Interest Rate on Deposits

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

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

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

Panel A: full sample

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

Panel B: metropolitan statistical areas

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

Panel C: micropolitan statistical areas

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

Panel D: rural areas

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

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

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

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

Table B.4: **Real Effects**

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

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

C Event Studies

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

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

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

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

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

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

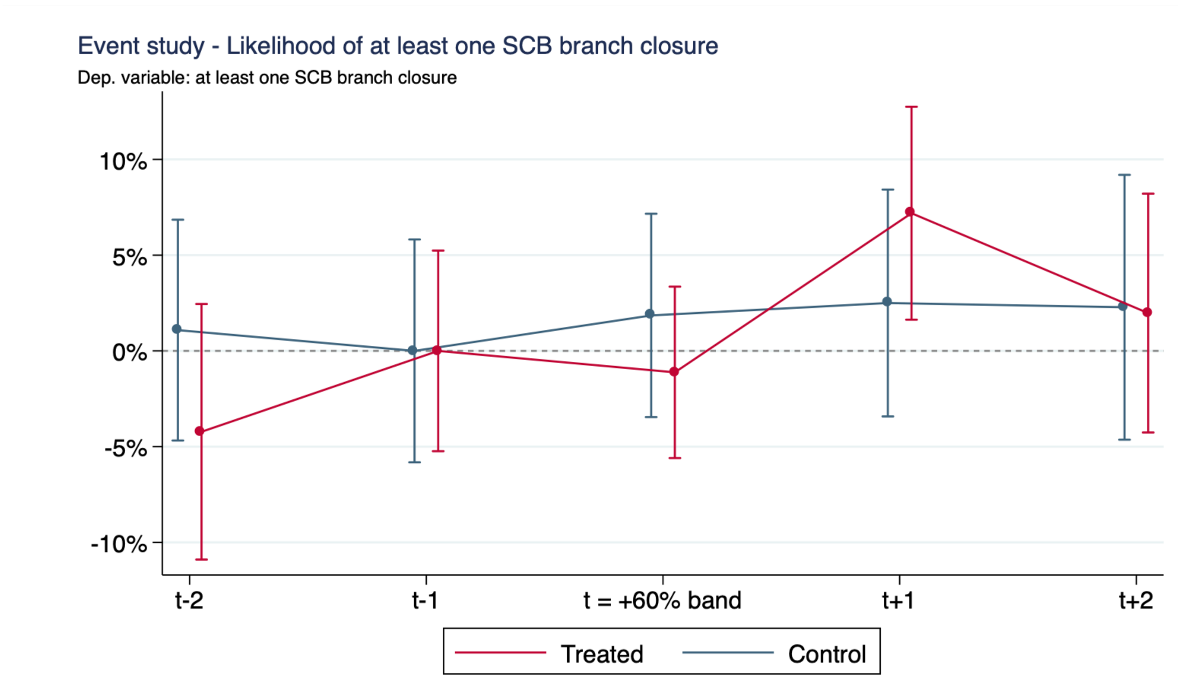


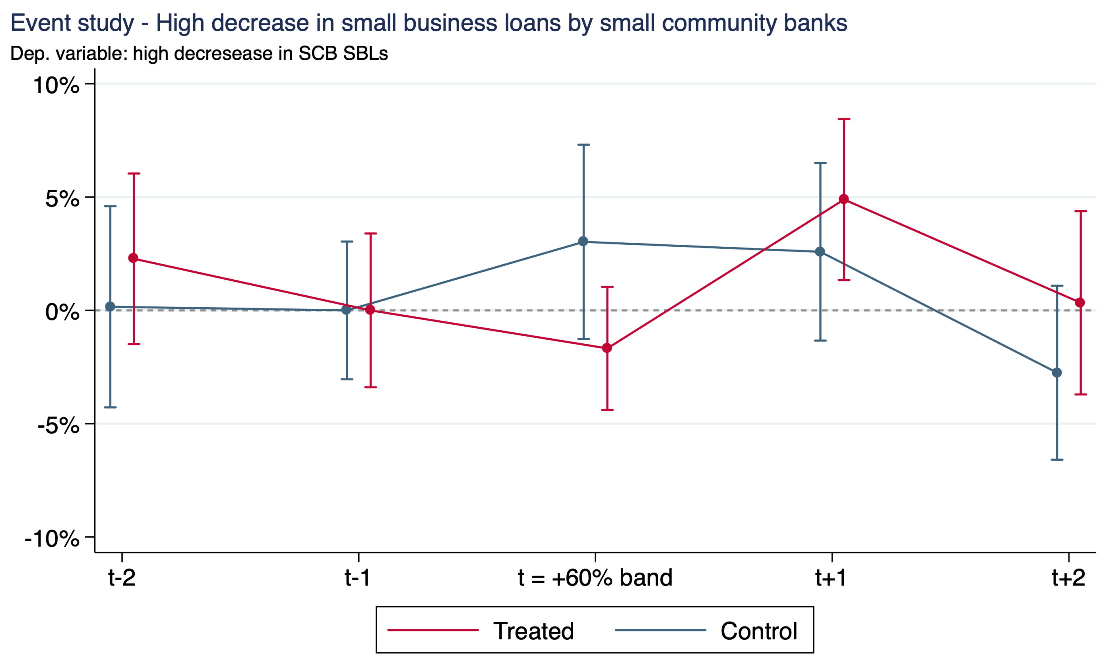
Table C.2: **Event Study: Small Community Bank Small Business Lending**

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

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

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

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



D IV analysis

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

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

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

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

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

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

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

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

The Financial Restitution Gap in Consumer Finance:

Insights from Complaints Filed with the CFPB*

Charlotte Haendler† Rawley Z. Heimer‡

Boston College Boston College

Abstract

Consumers seek restitution for disputed financial services by filing complaints with the Consumer Financial Protection Bureau (CFPB). We find that filings from low-income and Black zip codes were 30% less likely to be resolved with the consumer receiving financial restitution. The gap in financial restitution was scarcely present under the Obama administration, but grew substantially under the Trump administration. We attribute the change in financial restitution under different political regimes to companies *anticipating* a more industry-friendly CFPB, as well as to the more industry-friendly leadership of the CFPB achieving less financial restitution for low-income and Black filers. The financial restitution gap cannot be explained by differences in product usage nor the quality of complaints, which we measure using textual analysis.

Keywords: Consumer Finance, Financial Regulation, Financial Disputes, Discrimination, Textual Analysis

---

*We thank Taylor Begley, Patricia McCoy, and Amiyatosh Purnanandam for helpful feedback. Roshan Taroll provided fantastic research assistance. Any remaining errors or omissions are the authors' responsibility.

†Boston College, Carroll School of Management. Phone: +1 (216) 774-XXXX, Email: haendler@bc.edu

‡Boston College, Carroll School of Management. Phone: +1 (216) 774-2623, Email: heimer@bc.edu

1 Introduction

A robust economic literature studies differences in financial outcomes across socioeconomic groups and for racial minorities. Some of this literature specifically focuses on differences in the supply of financial services (e.g., differences in the supply of mortgage credit; Munnell et al., 1996). Another segment of the literature studies differences in the decision-making of individuals (e.g., low-socioeconomic status individuals have more pessimistic beliefs; Das et al., 2020). In response to these differences, policy-makers have proposed and implemented a wide-ranging set of rules and regulations. Regulatory agencies have been formed with the task of enforcing regulations and addressing issues with consumer financial products. Despite such interest, the literature has yet to study whether there are disparities in the outcomes of consumers' efforts, aided by regulators, to seek financial restitution in disputes with financial services companies.

The importance of consumers' efforts to seek financial restitution goes far beyond the wealth transfer between consumers and financial service firms. More broadly, there are crucial questions about the growth over the past several decades in the financial services sector and the share of economic surplus captured by financial firms (Greenwood and Scharfstein, 2013). Some research has argued that the growth of the financial services sector has not been matched with gains in efficiency (Zingales, 2015; Philippon, 2015; Heimer and Simsek, 2019). As such, understanding consumers' efforts to seek financial restitution provides insight into the economic bargaining power of consumers relative to suppliers of financial services, with a particular emphasis on the variation across consumer demographics.

To shed light on these questions, this paper studies the distribution of outcomes that result from consumer complaints submitted to the Consumer Financial Protection Bureau (CFPB). Since near its founding in 2011, the CFPB provides services for consumers to file disputes against financial service providers. The CFPB makes available to the public an anonymized and limited version of the filing in what it calls its database of consumer complaints. As of this writing, there were approximately 1.5 million complaints directed at companies that provide financial services on products ranging from mortgages, to students loans, to credit reporting. The database includes limited demographic information on the filers. Most important for our purposes, the database contains the zip code of the filer which we then match to geographic demographic information from the U.S. Census.

We find striking differences in the propensity to receive financial restitution from complaints submitted to the CFPB. On average, consumers receive financial restitution on approximately 5% of the filings. We are unable to say whether the 5% baseline is a large or small number, because consumer filings contain a mix of complaints that would merit financial restitution and ones that would not. However, taking the 5% as a baseline, we find that consumers from low-income areas and high-Black population percentage areas are significantly less likely to receive financial restitution. Complaints from the lowest quintile of household incomes and highest quintile of Black population are approximately 30% less likely to receive financial restitution than complaints from high-income and low-Black population share zip codes.

Next, we study several explanations for the differences in financial restitution. Though the limited nature of the data prevents us from definitive conclusions, we study the most plausible explanations. Among these explanations, we find the strongest support for the hypothesis that the political preferences of the Executive Branch affect how conciliatory financial service providers are towards consumers that file complaints.

We find evidence that the differences in financial restitution can be attributed to how financial service providers respond to the preferences of different political regimes. Because the CFPB is a federal regulatory agency, it is influenced by the preferences of elected officials, most crucially of the Executive Branch. The CFPB began under the Obama administration and the Trump administration took control thereafter. We find that complaints filed during Trump administration are 30% less likely to result in financial restitution. The reduced propensity to receive financial restitution is significantly larger for low-income and high-Black population areas. In fact, the differences across income and racial status are hardly present under the Obama administration.

The reduction in overall financial restitution under the Trump administration is not surprising, but the disproportionate effects on low-income and Black groups is more difficult to explain. Though we cannot provide direct evidence of the following theory, an intuitive explanation is that high-income, non-Black filers have more bargaining power with financial service providers because they could be making up a larger share of revenue and related services. For example, depository banks often offer tiers of service that depend on the amount of money the client has with the bank. In support of this explanation, we observe that the reduction in financial restitution begins around the time of Trump's election, as opposed to when the Trump administration changed the leadership of the CFPB to Mick Mulvaney from Obama appointee Richard Cordray. This suggests that financial service providers *anticipated* that the Trump administration would be more industry-friendly and responded to his election by becoming less accommodating of consumers, even though the CFPB had not yet changed its leadership.

We consider other explanations as well. The differences in financial restitution are unlikely to be caused by differences in the quality of the filings. We use textual analysis to assign readability scores to the text of the filing. We do not find large differences in the 'quality' of the writing of the complaints across income and racial status, nor do we find changes in the written text during the Trump administration. We also do not find differences in the propensity for filers to make references to seeking reimbursements for services. The results are also unlikely to be caused by differences in the types of financial products that consumers file complaints about. We find income and racial differences in financial restitution after the Trump administration across the majority of products.

Furthermore, we use event study analysis to test for differential effects during large settlements that involved the CFPB. In particular, we study a large settlement with Navient, a private provider of student loans, and with Wells Fargo, a large commercial bank that was found to have signed up their customers to fraudulent accounts. We find that these instances of financial misconduct increased the rate of complaints filed with the CFPB against these companies, consistent with the CFPB enforcement actions increasing the rate of attention. High- and low-income consumers as well as consumers that are less and more likely to be Black given their filing zip code are similarly affected by the events, both in the rate of new filings and propensity to receive financial restitution. These results imply that consumers from all backgrounds benefit when the CFPB has an active presence in resolving disputes.

Our paper contributes to a growing literature on disparities in financial outcomes by socioeconomic status. One stream of literature studies differences in individual characteristics and its effect on financial outcomes. These papers find differences in risk taking (Beshears et al., 2015; Kuhnen and Miu, 2017), expectations (Das et al., 2020), and financial literacy (Bernheim and Garrett, 2003; Lusardi et al., 2017). Related, a long literature studies how the supply of credit can be different for different socioeconomic and race groups. Most notably, there are long-running differences in the propensity for racial minorities to obtain mortgages. This literature extends from historical differences, such as redlining (Appel and Nickerson, 2016; Aaronson et al., 2017), to modern-day gaps in credit access.[1] Another literature studies broader differences in access to financial services (see e.g., Brown et al., 2019). To the best of our knowledge, Begley and Purnanandam (2020) is the only other paper to uses the CFPB complaints database. However, they focus on mortgage-related complaints, use the number of complaints in a zip code to proxy for the 'quality' of financial services, and study a fundamentally different question – how regulations affect the supply of financial services. Our paper looks at *all* categories of consumers' filings. We study the

[1]The literature on socioeconomic differences in mortgage credit is lengthy. The literature starts with papers such as Berkovec et al., 1994; Munnell et al., 1996; Tootell, 1996; Berkovec et al., 1998; Ladd, 1998. A more recent literature seeks to understand the effects of institutional characteristics on outcome disparity (see e.g., Bayer et al., 2018; Ambrose et al., 2020; Bhutta and Hizmo, 2020), and some particularly emphasize the role of technology (see e.g., Fuster et al., 2017; Buchak et al., 2018; Bartlett et al., 2019). Giacoletti et al. (2020) examines the effects of performance incentives on lending discrimination.

outcomes of these filings and, to the best of our knowledge, we are the only paper to document large differences in financial restitution across income and race groups.

Second, our paper segues with the literature in political economy that studies the malleability of the federal regulatory agencies and political influence on the federal bureaucracy. Akey et al. (2020) shows that banks that have connections to powerful politicians reduce efforts to comply with regulations that encourage lending to low socioeconomic, minority communities. Related papers show federal agencies in the U.S. and in other countries can give preferential treatment to politically connected firms (see e.g., Fisman and Wang, 2015; Mehta and Zhao, 2020; Mehta et al., 2020).

Finally, our paper relates to the literature on financial misconduct with a particular focus on dubious and fraudulent business practices targeted toward households. This literature can be traced to research on payday lenders. Several papers suggest that payday lenders take advantage of unsophisticated borrowers.[2] More recently, an emerging literature studies the financial misconduct of financial advisers (Gurun et al., 2018; Dimmock et al., 2018; Egan et al., 2019a), while other papers study the sale of worthless financial products to susceptible individuals (Rantala, 2019; Li et al., 2019). To the best of our knowledge, there are just three papers that directly study financial disputes between individuals and financial firms. Egan et al. (2019b) studies arbitration between consumers and financial advisers. They show that firms choose industry-friendly arbitrators and that uninformed consumers lose out. Cheng et al. (2020) and LaVoice and Vamossy (2019) study court judgments on debt collection cases in Missouri. LaVoice and Vamossy (2019) specifically documents racial disparities in court outcomes. Relative to these papers, our analysis of the CFPB data comes from a setting that includes a broad selection of financial products and where consumers do not need to go through formal legal proceedings. As such, our paper speaks to a broader class

[2]The literature on payday lending is lengthy. It includes the following papers listed in chronological order: Melzer, 2011; Morse, 2011; Bertrand and Morse, 2011; Dobbie and Skiba, 2013; Carrell and Zinman, 2014; Bhutta, 2011; Baugh, 2016; Carter and Skimmyhorn, 2017; Skiba and Tobacman, 2019; Fedaseyeu, 2020. Our apologies to other papers that we may have overlooked.

of financial outcomes and focuses on the role that regulators have in resolving disputes between consumers and firms.

The paper proceeds as follows. Section 2 describes the CFPB data. Section 3 documents income- and race-based differences among financial restitution recipients. Section 4 explores explanations for these socioeconomic differences. Section 5 describes evidence from two high-profile settlements with the CFPB. Section 6 concludes and discusses policy recommendations.

2 Consumer Complaints Data from the CFPB

The data come from the website for the Consumer Financial Protection Bureau (CFPB). Since its inception in 2011, the CFPB website contains a portal to submit complaints against financial service providers. Approximately 80% of complaints are submitted via the portal and our Internet Appendix illustrates the different steps the online submission entails. The remaining 20% are submitted via e-mail, fax, phone, postal mail or referral. In general, the submission process is as follows. First, the filer identifies the product or service that best matches the complaint. Second, the filer describes the problem both using a form provided by the CFPB and a narrative free-form response. Finally, the filer identifies the company that is the subject of the complaint and submits their contact information. The CFPB then passes the complaint on to the company and works to get a response to the consumer within 15 days.

The CFPB public database contains all complaints submitted via any means, but presumably to protect the anonymity of the consumer, it includes limited information on the demographics of filers. The data include the zip code of the filer (sometimes only the first three digits of the zip code), an indicator variable for whether the filer is elderly, and an indicator for whether the filer is a service member or veteran. Because of the limited demographic information, we use the U.S. Census to match demographics to zip codes. Specifically, we match the zip code of the filer to the zip code's corresponding county median household incomes and share of residents that are

Black.[3] We match complaints data at zip code level to census data at county level to overcome the lack of a standard correspondence between the U.S. Census' ZIP Code Tabulation Areas and the complaints' U.S. Postal Service ZIP Code.

Our analysis includes all complaints filed between January 2014 and March 2020.[4] Furthermore, for the early years of our sample, we reconcile the initial product and subproduct categorization to the one the CFPB has changed to in April 2017 and used ever since.

Figure 1 shows the ways in which complaints filed to the CFPB are resolved. Complaints can be resolved in the following ways: *Closed*, *Closed with explanation*, *Closed with monetary relief*, *Closed with non-monetary relief*, and *Untimely response*. The majority of complaints, 80.34%, are closed when the provider explains to the consumer the issue they raised with the financial product or service. We are primarily interested in complaints that are resolved with monetary relief for the consumer; these account for 5.06% of all complaints. Unfortunately, we do not know the size of the financial restitution paid to the consumer.

Complaints are filed on a range of products. Table 1 shows how complaints are distributed across the range of products. The largest categories of complaints are *Credit reporting, credit repair services, or other reports*, *Mortgage*, and *Debt collection*. These categories constitute 36.25%, 15.35%, and 20.30% of all complaints, respectively. The other categories include issues with bank accounts and credit cards, as well as consumer loans such as student, auto, and payday loans.

Notably, 39% of complaints contain a narrative written by the filer. Narratives are publicly disclosed, with the consent of the filer, only for complaints filed since March 2015. The following analysis uses the text of these complaints in a few ways (the remaining 61% of filings are likely

[3]When the CFPB reports a three-digit zip code, we average the demographics of the potential corresponding counties by their population size. When a zip code spans more than one county, we average the counties' demographics by their corresponding zip code's residential ratio values.

[4]Our analysis excludes consumer complaints filed before 2014. We make this sample restriction for two reasons. First, these observations are more likely to have missing information in the complaint. Second, these observations contained several discontinuities that give us cause to think that the publication of data during the nascent years of the CFPB was not random. This sample restriction removes approximately 180,000 complaints from our analysis. Nonetheless, all of the conclusions we draw from the data are robust to this sample restriction though we think the restricted sample gives a more accurate assessment of the magnitudes of the results.

to also contain a written narrative that has not been disclosed). First, we analyze the text to create measures of the "quality" of the complaint. Such measures are based on the quality of the written narrative. They proxy for how capable the consumer would be at describing the dispute with the financial service provider. Second, we use the text to conduct word searches for important subject matters within the complaint. In particular, we search for words that relate to "refund" to indicate that a filer expects to receive financial restitution from the company. We search for words that relate to "fraud" because the CFPB has been tasked with resolving instances of fraud.

In light of prior work using the CFPB data (Begley and Purnanandam, 2020), we augment the data with a measure of credit access. We proxy for credit access in local areas by using data on mortgage applications from the Home Mortgage Disclosure Act (HMDA). Specifically, we use HMDA data to calculate the average approval rate of mortgage applications in a given zip code.

3 The Financial Restitution Gap

In the section, we study the propensity to receive financial restitution as a result of filing complaints to the CFPB. We find stark differences in the propensity to receive financial restitution across demographic groups.

3.1 Graphical evidence

Figure 2 sorts complaints into quintiles based on the demographics of the filer. Panel A sorts the data into quintiles based on the median household income of the zip code of the filer, from low to high. We find that the propensity to receive financial restitution is positively related to the income of the filer. Filers in the lowest quintile of incomes have 4.21% of their complaints resolved with financial restitution. The propensity to receive financial relief increases monotonically with increase in incomes. Filers in the top quintile of incomes have 6.26% of their complaints resolved with financial restitution. Therefore, taking 6.26% as a baseline, low income filers are 2 percentage points or 33% less likely to have their complaints resolved with financial restitution.

We find similar differences in financial restitution across races. Panel B sorts complaints into quintiles of the share of Black population in the zip code, from high to low. The share of complaints met with financial restitution decreases monotonically in the share of Black population. Financial restitution is granted for 3.95% of complaints filed by zip codes with the largest share of Black population. On the other hand, 5.92% of complaints filed in zip codes with the lowest share of Black population result in financial restitution. As such, filers from zip codes with the largest share of Black population are 33% less likely to receive financial restitution from their complaints.

3.2 Regression evidence

We augment the graphical analysis using a regression framework. We estimate the following regression model using OLS:

$$financial\ restitution = \gamma_t + \beta_1 \times demographics + \beta_2 \times controls + \varepsilon_i \tag{1}$$

where the dependent variable, *financial restitution*, is an indicator variable that equals one if complaint i was resolved with financial restitution. The independent variable of interest, *demographics*, is the demographic information of the filer. In some tests, we define *demographics* as the zip code's household median income, and in other tests, we define *demographics* as the fraction of the zip code's population that is Black, entering regressions with a negative sign. In all tests, we normalize *demographics* so that a one unit increase equals a one standard deviation increase. The regression includes a vector of control variables for the characteristics of the complaint and of the filer. It also includes a time fixed effect, γ_t.

The coefficient of interest in equation 1 is β_1. Each standard deviation increase in *demographics* increases the propensity to receive financial restitution by an amount equal to β_1. For example, consider a regression that sets *demographics* equal to minus the share of Black population in the zip code, normalized so that every unit increase is equal to a standard deviation increase. In this regression, β_1 is an estimate of how much the propensity to receive financial restitution increases as the share of the zip code's population that is Black *decreases* by one standard deviation. For a regression that sets *demographics* to be based on the median income in the zip code instead, β_1 is an estimate of how much the propensity to receive financial restitution *increases* as the zip code's household median income increases by one standard deviation.

In the following regression tables, we include different sets of controls to account for differences across filings in terms of local area credit conditions, filer characteristics, product type, and firms. In particular, column (1) starts by including year fixed effects, which are included in all subsequent specifications. Column (2) then adds our proxy for local area credit supply – the approval rate on mortgages in HMDA. Column (3) controls for whether the filer is of old age. Column (4) includes fixed effects for the nine types of financial products available in the database. Column (5) includes fixed effects for the financial services company that is the subject of the complaint. Column (6) includes all of the aforementioned controls and fixed effects. Across all specification, we cluster standard errors by the state of the filer.

We start by estimating the propensity to receive financial restitution across different household incomes. Table 2, Panel A, sets *demographics* equal to the median income in the filer's zip code. Across all specifications, we find large reductions in the propensity to receive financial restitution in low-income zip codes. The estimate of β_1 is between 0.001 and 0.006 and is statistically significant at the one percent level in all specifications. The estimated coefficient implies that each standard deviation increase in the zip code's median income increases the propensity to receive financial restitution by between 0.1 and 0.6 percentage points, which is sizable given that the average propensity to receive financial restitution is 5%. The coefficient estimates imply large differences between the lowest and the highest socioeconomic zip codes, which supports the graphical difference in Figure 2. For example, suppose that low-income zip codes are two standard deviations below the mean of zip codes incomes and that that high-income zip codes are two standard deviations above. Then, the coefficients imply that there is a 0.4 to 2.4 percentage point greater propensity to receive financial restitution in high-income zip codes.

Next, we estimate the propensity to receive financial restitution across races. Table 2, Panel B, sets the independent variable of interest equal to the fraction of the population in the filer's zip code that is Black, entering the regression with a negative sign. Similar to our findings using household incomes to proxy for socioeconomic status, we find that the propensity to receive financial restitution is negatively related to the percentage of Black population. The estimate of β_1 is also between 0.001 and 0.006 and is statistically significant at the one percent error level in all six specifications.

Though we find statistically significant and economically large estimates across all specifications, the range of coefficient estimates on *demographics* is large. Most notably, the coefficients in both panels tend to be close to 0.006 in columns (1) through (3) when we only have time fixed effects and controls for credit supply and the filer's age. The coefficients fall to between 0.001 and 0.002 when we include either company or financial product fixed effects (columns 4 through 6). Both fixed effects increase the explanatory power of the regression, as captured by large increases in the R-squared. At the same time, the reduction in the coefficient estimates when adding these variables is to be expected because low- and high-income, Black populations use different financial products, and accordingly, different firms supply different financial services. Nonetheless, the differences in financial restitution across demographic groups hold up to controlling for such differences in financial services. Yet, the estimates merit further robustness tests, which we explore in the next section.

3.3 Robustness of differences in financial restitution

We evaluate the robustness of the regression estimates using "specification curve" analysis (see Simonsohn et al., 2015 for the original application and Akey et al., 2020 for an application in a finance publication). The specification curve is a way to visualize how changing the assumptions about the correct specification of the regression affects the coefficient of interest. Our specification curves include 180 different estimates of equation 1 that use different combinations of (i) threshold for inclusion in the demographic indicators, (ii) the sample period for the filing, (iii) the choice of controls, and (iv) the characteristics of the complaint. To read the specification curve, its top panel contains the coefficient estimate ordered from largest to smallest (and an indicator for whether the estimate is statistically significant at the five percent error level). The bottom panel contains the combination of assumption (i) through (iv) contained in each specification. Note that the specification curve analysis is slightly different from the estimates of equation 1 in that we use categorical variables to define *demographics* rather than continuous variables. We do so to illustrate the monotonic effects of *demographics* on the propensity to receive financial restitution and to draw comparison to our motivating graphical evidence in Figure 2.

We gain several insights from the specification curve analysis (Figure 3). First, the positive relation between income and the propensity to receive financial restitution is extremely robust, as is the negative one between Black population percentage and the propensity to receive financial restitution. The estimate on *demographics* is negative and statistically significant in the vast majority of specifications (*demographics* is measured using incomes in Panel A and minus Black population percentage in Panel B). Second, increasing the threshold for inclusion in the *demographics* indicator tends to make the coefficient estimate more negative. This further confirms that the propensity to resolve complaints with financial relief declines as the filer's zip code contains more individuals with low-income or more likely to be Black. Third, we use the specification curve to examine the effects of different sample periods by dividing the data into complaints resolved during the Obama and during the Trump presidencies. The results clearly show that the negative effect is larger during the Trump administration. We explore this result in more detail in the following section. Fourth, controlling for other characteristics of the filer does not have a large effect on the coefficient estimates. However, including state fixed effects shrinks the coefficients, presumably because many of the filings only contain the state or the first three digits of the zip code. Fifth, including fixed effects for the characteristics (company, product, or issue) of the complaint reduces the magnitude of the coefficient relative to not including these fixed effects. However, none of the three complaint characteristics is significantly more important than the others.

4 Explaining the Financial Restitution Gap

4.1 Political Influence on the CFPB

Regulatory agencies are malleable. Political leadership can influence the focus and operations of federal agencies (see e.g., Akey et al., 2020). The CFPB was founded under the Obama administration and it was designed to be consumer-friendly. The objectives of the agency changed when President Trump took office in January 2017. The Trump administration is widely thought to have negative views of regulations that are directed at firms. In this section, we examine whether the different political regimes affected the financial restitution gap.

We find that differences in financial restitution are significantly larger under the Trump administration, and for the most part, were barely present under the Obama administration. Figure 4 sorts the percentage of complaints that receive financial restitution by demographic information and by political administration. Panel A sorts complaints into quintiles accoding to corresponding household median incomes of the zip code of origination, from low to high. During the Obama administration, 6.9% of complaints in the top quintile of incomes and 5.47% of complaints in the bottom quintile receive financial restitution. Under the Trump administration, 5.78% of complaints in the top quintile and just 3.48% of complaints in the bottom quintile receive financial restitution. As such, the socioeconomic gap of 1.43 ppt grows to 2.3 ppt from the Obama to Trump administration.

The political effects are even more stark when we examine differences across races. Figure 4, Panel B sorts complaints into quintiles according to the corresponding share of population that is Black in the zip code of origination, from high to low. During the Obama administration, 6.41% of complaints in zip codes with the fewest Black individuals and 5.77% of complaints in zip codes with the largest share of Black population receive financial restitution. During the Trump administration, 5.54% (3.04%) of complaints in the quintile with the fewest (largest) share of Black population receive financial restitution. Therefore, a financial restitution gap of 0.64 percentage points under the Obama administration grows to 2.5 percent points under the Trump administration.

We find that low-income zip code quintiles and high-Black population percentage zip code quintiles are significantly less likely to receive financial restitution under the Trump administration. We further corroborate this result by controlling - to the extent possible - for the evolution of population filing rates across demographics over time in Appendix 1.[5]

Table 3 uses regression analysis to explore the effects of changes in political regimes on the differences in financial restitution. Panel A uses median income and Panel B uses the share of Black population. Columns (1) and (2) estimate the regression specification in equation 1 on the sample of complaints resolved during the Obama administration and during the Trump administra-

[5]In the Appendix we explore filing rates across the demographics' distributions. We observe a U-shaped pattern where both the highest and lowest quintiles are more likely to file complaints with the CFPB. We also observe that there is a larger increase in the filing rates of low-income and high-Black population areas occurring during the Trump administration. Though this might explain the change in financial restitution across different political administrations, we find that the response to the Equifax data breach in 2017 explains the change in filing rates, and not the change in financial restitution. The increase in filing rates starting in 2017 is isolated to credit reporting, is directed toward the major credit bureaus, and comes mostly from low-income and high-Black population areas. Furthermore, our main results on financial restitution differences hold after we exclude credit reporting from the analysis.

tion, respectively. Columns (3) and (4) use the following difference-in-differences regressions:

$$financial\ restitution_{i,t} = \gamma_t + \beta_1 \times demographics_i + \beta_2 \times post\ Trump_t + \dots$$
$$\dots + \beta_3 \times demographics_i \times post\ Trump_t + \beta_4 \times controls + \varepsilon_{i,t} \quad (1)$$

where *post Trump* is an indicator for resolving the complaint after January 20, 2017. The independent variable of interest is the interaction between *demographics* and *post Trump*. The coefficient estimate β_3 captures the marginal effect of the Trump administration on the relation between the demographics and the propensity to receive financial restitution.

The regression analysis supports our graphical evidence that the difference in the propensity to receive financial restitution emerges primarily under the Trump administration. In the split sample tests in columns (1) and (2), the coefficient estimates on *demographics* is larger during the Trump administration sample than for the Obama administration sample. When *demographics* is defined as median income (Panel A), the coefficient is 0.0044 under the Obama administration and 0.0074 under the Trump administration. The difference between administrations is larger when *demographics* is defined as Black population percentage, entering regressions with a negative sign (Panel B). The coefficient estimate is 0.0023 under Obama and 0.0084 under the Trump administration. All of the coefficient estimates are statistically significant.

Moving to the difference-in-differences estimates of β_3, they also support the conclusion that the restitution gap widens under the Trump administration. These coefficients capture the difference between Presidential administrations in how demographic variables affects the propensity to receive financial restitution. The coefficient estimates are all positive, suggesting that high-income status filer are relatively more likely to receive financial restitution under the Trump administration. However, including granular fixed effects for the company reduces the size of the estimates and they lose statistical significance when *demographics* is measured by zip code median incomes.

This could be caused by a change across administrations in the composition of companies that were the subject of complaints, a prospect we later explore.

Given the change in preferences between the Obama and Trump administrations, it is not surprising that the overall propensity for consumers to receive financial restitution declines under the Trump administration. Less clear, however, is why low-income and Black filers experienced a larger decline under the Trump administration than did high-income and non-Black filers.

First, we use event-study regressions around the change in presidential administrations to shed light on how the differences in financial restitution took hold. Figure 5 plots distributed lagged coefficients for each quarter relative to the first quarter of 2014. Panel A plots the propensity to receive financial restitution in a given quarter for *all filers* relative to the first quarter of 2014. Panels B and C compare how the differences across filers' demographics change over time. Panel B sets *demographics* equal to the zip code's median income and Panel C sets *demographics* equal to the share of the zip code's population that is Black, entering underlying regressions with a negative sign. These panels use coefficient estimates to show how the differences in financial restitution change over time. Negative coefficient values in, e.g., panel B indicate that low-income filers are less likely than high-income filers to receive financial restitution.

We start with Panel A, where the coefficient estimates indicate the change in propensity to receive financial restitution for filers from all zip codes. There is a sharp drop of approximately two percentage points in the propensity to receive financial restitution starting in the quarter after Trump is inaugurated. Prior to Trump's inauguration, the coefficient estimates are not statistically different from zero, which indicates that there are no pre-trends in the dependent variable. Notably, the decrease in financial restitution occurs after the Trump inauguration and before the Trump administration changed the leadership of the CFPB (from Obama administration holdover, Richard Cordray, to acting director, Mick Mulvaney, in the last quarter of 2017). This suggests that, though leadership of the CFPB had not yet changed, the propensity for companies to give financial restitution declined significantly. This result is consistent with the explanation that financial service companies expected the CFPB to be less consumer-oriented under the Trump administration and became less willing to provide financial restitution as a result. Panels B and C confirm that the differences in financial restitution are mostly stable under the Obama administration and occasionally statistically different from zero. The differences appear to strengthen under the Trump administration, although they also develop at the peak of the 2016 election cycle, before Trump was elected. Thus, the heightened political uncertainty during this period may have encouraged companies that have low-income and large Black clientele to bet that the CFPB would reduce their enforcement of complaints.

Next, we study the mechanism through which the CFPB would have changed its enforcement of complaints between the Obama and Trump administrations. We consider two possibilities: (1) the CFPB became favorable toward the types of financial products that are more likely to be used by low-income and Black consumers and (2) we consider whether the CFPB became more favorable to certain companies or whether the reduction in enforcement was broadly applied.

We address both possibilities by examining the propensity for firms to grant financial restitution across the two political regimes. Figure 6 presents a bar graph of the percentage of firms that resolve at least one complaint with monetary relief. The bar graph is sorted by the product each firm has received the most complaints about and into complaints filed during the two presidencies. The key feature of the data in this graph is that we keep only the set of firms that have received at least one complaint during both presidencies.

We find that the reduction in the propensity to grant financial restitution during the Trump administration is broadly applied across all financial product categories. Across all nine of the categories, except for *money transfers*, we find reductions in the propensity for firms to grant financial restitution under the Trump administration. The second largest reduction in the propensity for firms to grant financial relief is in the student loan category, a finding that is broadly consistent with the lenience toward private student loan providers demonstrated by the Department of Education under the Trump administration.[6] We interpret this result as evidence that financial service providers broadly expected less enforcement under the Trump administration and as a result, adjusted their propensity to award financial restitution to customers.

Next, we explore how the within-category change in the propensity to grant financial restitution relates to the financial products used by low-income and Black individuals. First, we show that there are differences in the types of financial products used by the two different demographic groups. Figure 7 shows that low-income and Black groups make up a larger share of complaints to the CFPB on products like credit reporting, debt collection, and vehicle loans/leases. On the other hand, high-income and non-Black groups constitute a relatively larger share of complaints about mortgages, money transfers, and credit cards. However, these differences in product usage are moderately sized. For example, zip codes with the highest quintile of Black population percentage make up 23% of complaints about credit reporting and 15% of the complaints about credit cards (relative to a 20% baseline if complaints were randomly assigned across demographic groups).

Despite these differences in product usage across demographics, they cannot explain the differences in financial restitution across presidential administrations. In Figure 8, each data point corresponds to one of the nine categories of complaints. The x-axis is the share of complaints filed by low-income and Black zip codes. The y-axis is the change from the Obama to the Trump administration in the propensity to resolve complaints with financial restitution. If the Trump administration was primarily targeting low-income or Black consumers, then we would expect to see the CFPB weaken its enforcement efforts on targets that are primarily used by such consumers. For example, the CFPB would allocate resources away from debt collection and vehicle loans/leases toward resolving disputes in mortgage and credit card products. However, these graphs show that there is no relation between the change in the propensity to give financial restitution and the share of low-income and Black filers (incomes in Panel A and race in Panel B). This result further sug-

[6]For example, "With veto, Trump backs DeVos in battle over relief for scammed student-loan borrowers" Marketwatch, Published: May 30, 2020 at 2:47 p.m. ET, By Jillian Berman.

gests that financial service firms broadly expected the CFPB to be weaker in resolving disputes, rather than the CFPB making targeted efforts to reduce its assistance to low-income and Black filers.

Finally, we provide further evidence that financial service providers broadly changed their propensity to grant financial restitution when the presidential administration changed from the relatively consumer-friendly Obama administration to the relatively industry-friendly Trump administration. Table 4 presents estimates of the interaction coefficient on *demographics* and *post Trump* from equation 1. In these regressions, we sort the data into sub-samples for the size of the company and the company's propensity to grant financial restitution during the Obama administration. We sort companies into those that had fewer than 25 complaints, between 25 and 100, between 100 and 1,000, and greater than 1,000 during the Obama administration. We also sort companies by whether they gave no financial restitution under the Obama administration, and whether they had above or below the median fraction of complaints resolved with financial restitution. This sorting is intended to capture whether some firms are more or less forthcoming towards consumers during the Obama administration.

We find that companies, regardless of whether they were more or less conciliatory towards consumers under the Obama administration, contribute to the financial restitution gap under Trump. We find positive estimates of the interaction coefficients in the majority of the sub-samples. Most strikingly, mid- to large-size firms are the most responsible for the effect. Companies with between 100 and 1,000 complaints have the largest and most consistent effects on the financial restitution gap. One surprising finding from these sub-sample results is that even companies that gave *no* financial restitution at all under the Obama administration contribute to the restitution gap that emerges under the Trump administration (see the first column of the table). This suggests that some of the no-financial-restitution companies under Obama began to provide financial restitution under Trump, but did so disproportionately to high-income, non-Black filers.

4.2 The Quality of Complaints to the CFPB

One possible difference across demographic groups in the propensity to receive financial restitution could be that complaints have different quality. For example, it could be that income correlates with financial sophistication and that less financially sophisticated individuals file complaints that have less grounds for restitution. Unfortunately, the data does not give clear guidance for which complaints have a legitimate reason to expect financial restitution. However, we use the data that is available to us: we estimate the quality of complaints using the textual descriptions of the complaints. An important caveat is that we cannot directly use textual analysis to quantify which complaints are more or less deserving of financial restitution. We can only use textual analysis to determine whether there are differences across demographic groups in the content of the complaints. To preview the results of the following analysis, we find that filers across different demographic groups write similar texts in their complaints.

We first focus on the length of the complaints to assess whether there are fundamental differences in how filers are voicing their discontent across demographics. The length of the complaint is a simple count of the words contained in the narrative. Table 5, Panel A uses regression analysis where the dependent variable is the number of words in the text of the complaint and the independent variable of interest is *demographics*. We find that complaints from low-income and high-Black population percentage zip codes average the same number of words as those from high-income, low-Black population percentage zip codes. Furthermore, we use interactions between *demographics* and *post Trump* to test if there are changes to the text of the complaints across demographic groups for those filed after the Trump administration. The regressions show that complaints from from zip codes with a lower share of Black population contain more words during the Trump administration. However, the size of the coefficient is small compared to the average narrative length in the sample. Overall, the results suggest that the content of the complaints do not change significantly between presidential administrations. As such, the demographic differences in financial restitution that emerge under the Trump administration are unlikely to be explained by changes to the complaints submitted by consumers.

To further investigate the quality of the complaints, we look at their complexity. We use two measures that were developed in the linguistic literature and have been used in the finance literature as well.[7] The first measure is the Flesch reading ease score, which ranges from 0 to 100, with 100 being the highest readability/lowest complexity score. For reference, scoring between 60 to 70 is equivalent to writing complexity of school grade level 12 to 10. The Flesch reading ease score is computed as follows:

$$Flesch\_score = 206.835 - 1.015 \times \left(\frac{number\_of\_words}{number\_of\_sentences}\right) - 84.6 \times \left(\frac{number\_of\_syllables}{number\_of\_words}\right)$$

The second measure is the Gunning fog index, which ranges from 0 to 20, with 20 being the lowest readability/highest complexity score. For reference, scoring between 10 and 12 is equivalent to writing complexity of school grade level 10 to 12. The Gunning for index is computed as follows:

$$Gunning\_Fog\_index = 0.4 \times \left[\left(\frac{number\_of\_words}{number\_of\_sentences}\right) + 100 \times \left(\frac{number\_of\_complex\_words}{number\_of\_words}\right)\right]$$

where complex words are words with at least three syllables.

To facilitate comparability across measures, the Flesch reading ease score enters regressions with a negative sign. Hence, higher values in both indexes proxy for lower readability/higher complexity of the narratives.

[7] For a review of the finance literature using the two measures, refer to Loughran and McDonald (2016).

The regression results are presented in Table 5, Panels B and C. The findings on the quality of the complaints using these writing complexity measures as proxies are similar to the results using the simple word count. We find limited evidence that the complexity of the complaint is declining in the household median income of the filer. However, we do not find differences when looking at the share of Black population. We also do not find evidence of changes to the narrative complexity of the complaint before and after the Trump administration. We find no effects when considering Black population percentage and the effects are very small in magnitude when considering household median income. Overall, the evidence suggests that there is not much difference in the narratives of the complaints across demographic groups nor before and after the Trump administration took control of the CFPB.

4.3 The Content of Complaints

In this section, we inspect the content of the complaints. First, we inspect whether there are differences across demographic groups in the expectations of receiving financial restitution. We flag complaints that mention the word "refund" or other related words or concepts.[8] Table 6, Panel A presents regression analysis where the dependent variable is an indicator for mentioning "refund" or other related words or concepts. The independent variable of interest is *demographics* in its interaction with *Trump administration*. We find a slightly higher propensity to employ broad mentions of the "refund" concept in complaints originating from zip codes with high-income, low-Black population during the Trump administration. However, the magnitude is small and is unlikely to explain the differences in financial restitution across demographic groups. Generally,

[8]Related concepts for"refund": "refunding", "refunded", "refunds", "repay", "reimburse", "reimbursement", "reimbursements", "reimbursing", "reimbursed", "repayment", "repayments", "repaying", "pay back", "paying back", "paid back", "make good", "making good", "made good", "compensate", "compensation", "compensations", "compensating", "compensated", "recoup", "recoups", "recouping", "recouped", "remunerate", "remuneration", "remunerations", "remunerating", "remunerated", "squaring accounts with", "squared accounts with", "square accounts with".

different demographic groups appear to expect similar levels of financial restitution from their filings to the CFPB.

Next, we assess whether the complaints relate to fraudulent activities by the financial service firm. We search the text of the complaint for the word "fraud" and fraud-related concepts.[9] Using the same regression analysis as before, Table 6, Panel B shows that lower income filers are less likely to have complaints that relate to fraud. However, mentioning fraud becomes more likely during the Trump administration, which contrasts with our result that the gap in financial restitution becomes large after Trump became president. Also, filers from zip codes that have a higher share of Black population are not more likely to mention fraud. Combined, these results are unable to say that some demographic groups are less likely to be the target of outright fraud.

5 High-profile CFPB Cases

In this section, we examine the resolution of two large cases brought by the CFPB against financial service providers. We study how the resolution of the cases and the filings to the CFPB vary across demographic groups. This sheds light on how consumers respond to news about high-profile cases and the financial restitution that results from the cases.

The first case we study involved Navient, one of the largest private providers of student loans. In January, 2017, the CFPB filed a lawsuit against Navient accusing the company of engaging in a multitude of deceptive practices that were not in the best interest of its customers. The case played out slowly over the subsequent three years, but ultimately, Navient was not made to issue financial restitution to any of its clients.

Figure 9 plots complaints against Navient and the complaints resolved with financial restitution over the course of time. The graph sorts complaints into those coming from zip codes with

[9] Related concepts for "fraud": "deceit", "deception", "trickery", "rip-off", "fake", "con", "impostor", "fraudster", "deceive", "deceiving", "deceived", "defraud", "defrauded", "cheat", "cheating", "cheated", "trick", "tricked", "tricking", "mislead", "misled", "misleading", "misguide", "misguided", "misguiding".

median incomes greater than or less than 50,000 (Panel A) and into zip codes with at least or less than 25% of the population being Black (Panel B). In these graphs, we plot the cumulative density of the complaints, but we set the month prior to the initial lawsuit against Navient as being equal to 100%. All other data points are percentages relative to this month. The graph shows that there is a large spike in complaints in the month of the lawsuit – the number of complaints rose by 30% relative to the total number of complaints filed up to December 2016. The CFPB received a steady increase in complaints in the months that followed. Because Navient claimed to have done nothing wrong, and eventually settled without issuing financial restitution, the number of complaints resolved with financial restitution is essentially constant around the time of the lawsuit.

Noticeably, there is scant difference across demographic groups in the number of complaints filed against Navient or in the propensity for Navient to issue financial restitution. We interpret this result as showing that Navient did not give favorable treatment to either high- or low- income and Black groups. The result also suggests that the different demographic groups had similar responses to the news about the Navient lawsuit. It is consistent with there not being a gap in awareness across filer demographics.

The second case study we consider involved Wells Fargo, a large commercial bank. In September 2016, the CFPB fined Wells Fargo $100 million for the widespread practice of opening unauthorized banking accounts on behalf of unknowing consumers. Wells Fargo was required to pay full refunds to consumers. The refunds would cover the costs of all monthly maintenance fees, insufficient fund fees, overdraft charges, and other fees they paid because of the creation of the unauthorized accounts. The CFPB expected the refunds to total at least $2.5 million.[10]

Figure 10 plots complaints against Wells Fargo and the complaints resolved with financial restitution over the course of time. The structure of the graph is the same as for the Navient figure, Figure 9. The key difference between the Wells Fargo and the Navient case studies is that Wells

[10]https://www.consumerfinance.gov/about-us/newsroom/consumer-financial-protection-bureau-fines-wells-fargo-100-million-widespread-illegal-practice-secretly-opening-unauthorized-accounts/

Fargo's "cross-selling" sales tactics were well-known to the public before the CFPB took action. As a result, there is a steady increase in the number of complaints filed against Wells Fargo before September 2016. The rate of cases that are resolved with financial restitution is also rising at the same rate as the number of filings. The CFPB actions against Wells Fargo leads to increases in the rate of new complaints, but the increase is not nearly as sharp as it was for Navient. However, like in the Navient case, we observe scant differences across demographic groups. This provides evidence of similar rates of attention by consumers from different backgrounds, as well as similar levels of treatment of complaints across demographic groups.

6 Conclusions

We study disputes between consumers and financial service providers. To do so, we use a database of complaints filed with the Consumer Financial Protection Bureau. We find that there are large differences across demographic groups in the propensity to receive financial restitution from a complaint despite no differences in the rate of filing a complaint. Complaints filed from the low-income zip codes or zip codes that have a larger share of Black population are approximately 30% less likely to be resolved with financial restitution. We explore various explanations for these findings. We find no differences across demographic groups in the attention paid to prominent actions against firms instigated by the CFPB, no differences in the measurable "quality" of the complaint, and no differences in the expectations of financial restitution in the text of the complaints. The most striking difference we observe is the change in the propensity to receive financial restitution under different political regimes. The CFPB gets companies to deliver financial restitution significantly more frequently under the Obama administration relative to under the Trump administration, and the reduction in financial restitution is especially prevalent for low-income and Black filers. We provide evidence that financial service firms expect the CFPB to reduce its enforcement of filings under the Trump administration.

There is a lengthy literature in economics and finance that documents disparate outcomes across demographic groups. This literature often searches for evidence of discrimination by economic decision-makers against minority groups. Our paper is notable in that we study a setting in which there is no *a priori* reason to expect disparate treatment. We study consumers that file complaints against financial service providers and these complaints are filed through a federal regulatory agency, the CFPB. We would have expected the federal agency to have leveled the playing field for low-income and Black filers. Instead, we find that high-income and non-Black filers are more likely to receive financial restitution from complaints they file to the CFPB. As such, we view our findings as a puzzle that should motivate future efforts to understand why financial regulators can have heterogeneous effects on consumer financial outcomes.

Our findings have important implications for the regulation of consumer financial products. Low-income and Black groups are likely to have less means to instigate recourse in disputes with firms. As such, they would be more reliant on the services of government agencies to handle any such disputes. However, federal agencies only provide such assistance when they have the support of elected officials. As such, the policy preferences of the federal government shape the distribution of outcomes via their influence on regulatory agencies. Firms change their behavior depending on their expectations of regulatory enforcement.

References

Aaronson, D., Hartley, D., Mazumder, B., 2017. The effects of the 1930s HOLC "redlining" maps. Working Paper .

Akey, P., Heimer, R. Z., Lewellen, S., 2020. Politicizing consumer credit. Journal of Financial Economics Forthcoming.

Ambrose, B. W., Conklin, J. N., Lopez, L. A., 2020. Does borrower and broker race affect the cost of mortgage credit? The Review of Financial Studies Forthcoming.

Appel, I., Nickerson, J., 2016. Pockets of poverty: The long-term effects of redlining. Working Paper .

Bartlett, R., Morse, A., Stanton, R., Wallace, N., 2019. Consumer-lending discrimination in the fintech era. Working Paper .

Baugh, B., 2016. Payday borrowing and household outcomes: Evidence from a natural experiment. Tech. rep., Working paper.

Bayer, P., Ferreira, F., Ross, S. L., 2018. What drives racial and ethnic differences in high-cost mortgages? the role of high-risk lenders. The Review of Financial Studies 31, 175–205.

Begley, T. A., Purnanandam, A., 2020. Color and credit: Race, regulation, and the quality of financial services. Journal of Financial Economics Forthcoming.

Berkovec, J. A., Canner, G. B., Gabriel, S. A., Hannan, T. H., 1994. Race, redlining, and residential mortgage loan performance. The Journal of Real Estate Finance and Economics 9, 263–294.

Berkovec, J. A., Canner, G. B., Gabriel, S. A., Hannan, T. H., 1998. Discrimination, competition, and loan performance in fha mortgage lending. Review of Economics and Statistics 80, 241–250.

Bernheim, B. D., Garrett, D. M., 2003. The effects of financial education in the workplace: Evidence from a survey of households. Journal of public Economics 87, 1487–1519.

Bertrand, M., Morse, A., 2011. Information disclosure, cognitive biases, and payday borrowing. The Journal of Finance 66, 1865–1893.

Beshears, J., Choi, J. J., Laibson, D., Madrian, B. C., Milkman, K. L., 2015. The effect of providing peer information on retirement savings decisions. The Journal of finance 70, 1161–1201.

Bhutta, N., 2011. The community reinvestment act and mortgage lending to lower income borrowers and neighborhoods. The Journal of Law and Economics 54, 953–983.

Bhutta, N., Hizmo, A., 2020. Do minorities pay more for mortgages? The Review of Financial Studies Forthcoming.

Brown, J. R., Cookson, J. A., Heimer, R. Z., 2019. Growing up without finance. Journal of Financial Economics 134, 591–616.

Buchak, G., Matvos, G., Piskorski, T., Seru, A., 2018. Fintech, regulatory arbitrage, and the rise of shadow banks. Journal of Financial Economics 130, 453–483.

Carrell, S., Zinman, J., 2014. In harm's way? payday loan access and military personnel performance. The Review of Financial Studies 27, 2805–2840.

Carter, S. P., Skimmyhorn, W., 2017. Much ado about nothing? new evidence on the effects of payday lending on military members. Review of Economics and Statistics 99, 606–621.

Cheng, H., Severino, F., Townsend, R. R., 2020. How do consumers fare when dealing with debt collectors? evidence from out-of-court settlements. Review of Financial Studies Forthcoming.

Das, S., Kuhnen, C. M., Nagel, S., 2020. Socioeconomic status and macroeconomic expectations. The Review of Financial Studies 33, 395–432.

Dimmock, S. G., Gerken, W. C., Graham, N. P., 2018. Is fraud contagious? coworker influence on misconduct by financial advisors. The Journal of Finance 73, 1417–1450.

Dobbie, W., Skiba, P. M., 2013. Information asymmetries in consumer credit markets: Evidence from payday lending. American Economic Journal: Applied Economics 5, 256–82.

Egan, M., Matvos, G., Seru, A., 2019a. The market for financial adviser misconduct. Journal of Political Economy 127, 233–295.

Egan, M. L., Matvos, G., Seru, A., 2019b. Arbitration with uninformed consumers. Working paper .

Fedaseyeu, V., 2020. Debt collection agencies and the supply of consumer credit. Journal of Financial Economics .

Fisman, R., Wang, Y., 2015. The mortality cost of political connections. The Review of Economic Studies 82, 1346–1382.

Fuster, A., Goldsmith-Pinkham, P., Ramadorai, T., Walther, A., 2017. Predictably unequal? the effects of machine learning on credit markets. Tech. rep., CEPR Discussion Papers.

Giacoletti, M., Heimer, R., Yu, E., 2020. Using high-frequency evaluations to estimate discrimination: Evidence from loan officers. Working paper .

Greenwood, R., Scharfstein, D., 2013. The growth of finance. Journal of Economic Perspectives 27, 3–28.

Gurun, U. G., Stoffman, N., Yonker, S. E., 2018. Trust busting: The effect of fraud on investor behavior. The Review of Financial Studies 31, 1341–1376.

Heimer, R., Simsek, A., 2019. Should retail investors' leverage be limited? Journal of Financial Economics 132, 1–21.

Kuhnen, C. M., Miu, A. C., 2017. Socioeconomic status and learning from financial information. Journal of Financial Economics 124, 349–372.

Ladd, H. F., 1998. Evidence on discrimination in mortgage lending. Journal of Economic Perspectives 12, 41–62.

LaVoice, J., Vamossy, D. F., 2019. Racial disparities in debt collection. Working paper .

Li, T., Shin, D., Wang, B., 2019. Cryptocurrency pump-and-dump schemes. Working Paper .

Loughran, T., McDonald, B., 2016. Textual analysis in accounting and finance: A survey. The Accounting Review 54, 1187–1230.

Lusardi, A., Michaud, P.-C., Mitchell, O. S., 2017. Optimal financial knowledge and wealth inequality. Journal of Political Economy 125, 431–477.

Mehta, M. N., Srinivasan, S., Zhao, W., 2020. The politics of m&a antitrust. Journal of Accounting Research 58, 5–53.

Mehta, M. N., Zhao, W., 2020. Politician careers and sec enforcement against financial misconduct. Journal of Accounting and Economics p. 101302.

Melzer, B. T., 2011. The real costs of credit access: Evidence from the payday lending market. The Quarterly Journal of Economics 126, 517–555.

Morse, A., 2011. Payday lenders: Heroes or villains? Journal of Financial Economics 102, 28–44.

Munnell, A. H., Tootell, G. M., Browne, L. E., McEneaney, J., 1996. Mortgage lending in Boston: Interpreting HMDA data. The American Economic Review pp. 25–53.

Philippon, T., 2015. Has the us finance industry become less efficient? on the theory and measurement of financial intermediation. American Economic Review 105, 1408–38.

Rantala, V., 2019. How do investment ideas spread through social interaction? evidence from a ponzi scheme. The Journal of Finance 74, 2349–2389.

Simonsohn, U., Simmons, J. P., Nelson, L. D., 2015. Specification curve: Descriptive and inferential statistics on all reasonable specifications. Unpublished working paper. New York University.

Skiba, P. M., Tobacman, J., 2019. Do payday loans cause bankruptcy? The Journal of Law and Economics 62, 485–519.

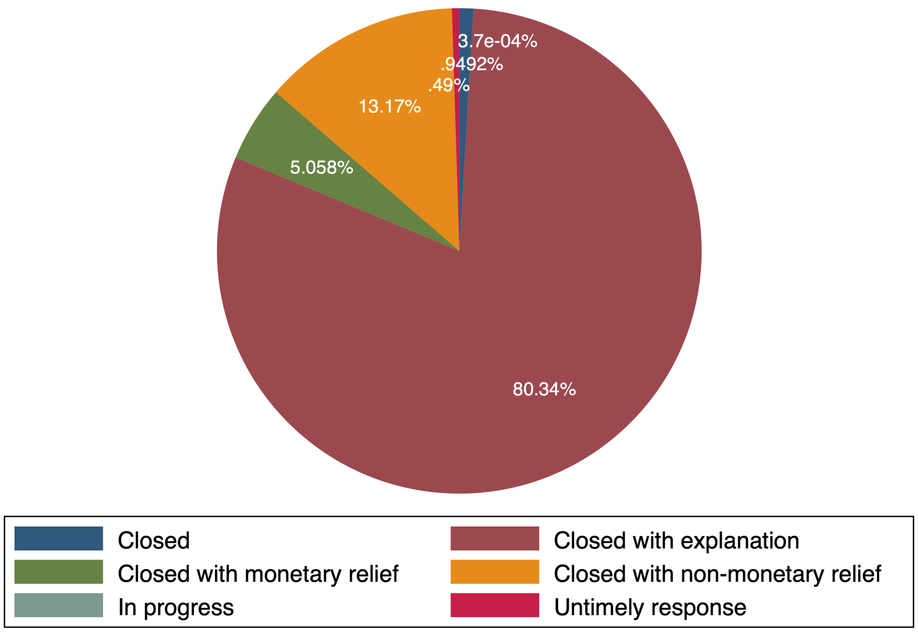
Tootell, G. M., 1996. Redlining in Boston: Do mortgage lenders discriminate against neighborhoods? The Quarterly Journal of Economics 111, 1049–1079.

Zingales, L., 2015. Presidential address: Does finance benefit society? The Journal of Finance 70, 1327–1363.

Figure 1: **Financial restitution of Complaints at the CFPB**

This Figure shows the main features of complaints' resolution. Panel A shows how complaints are resolved. Panel B shows how monetary relief is distributed across complaints related to different product categories.

Panel A: Resolution Across Complaints



Panel B: Financial Restitution Across Categories

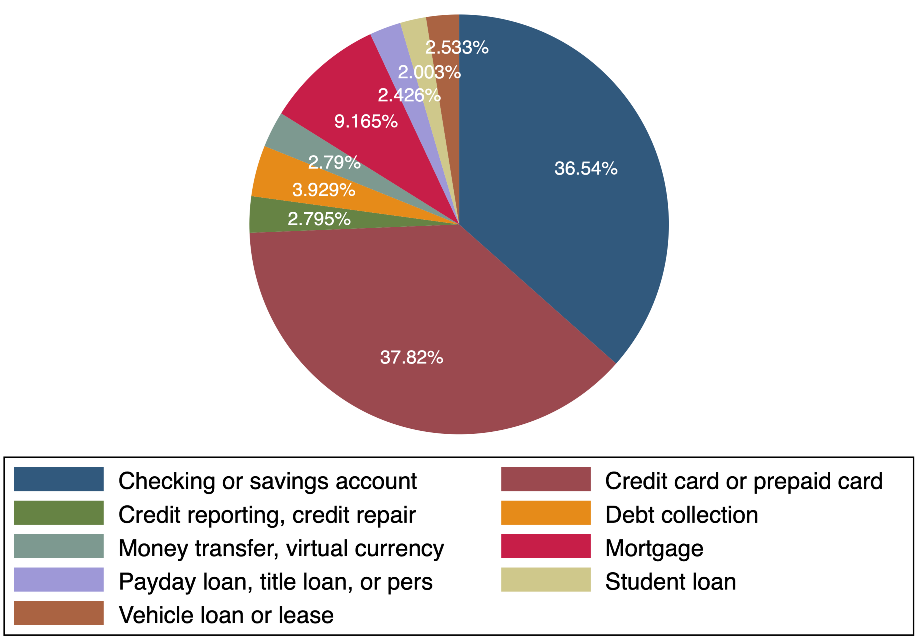
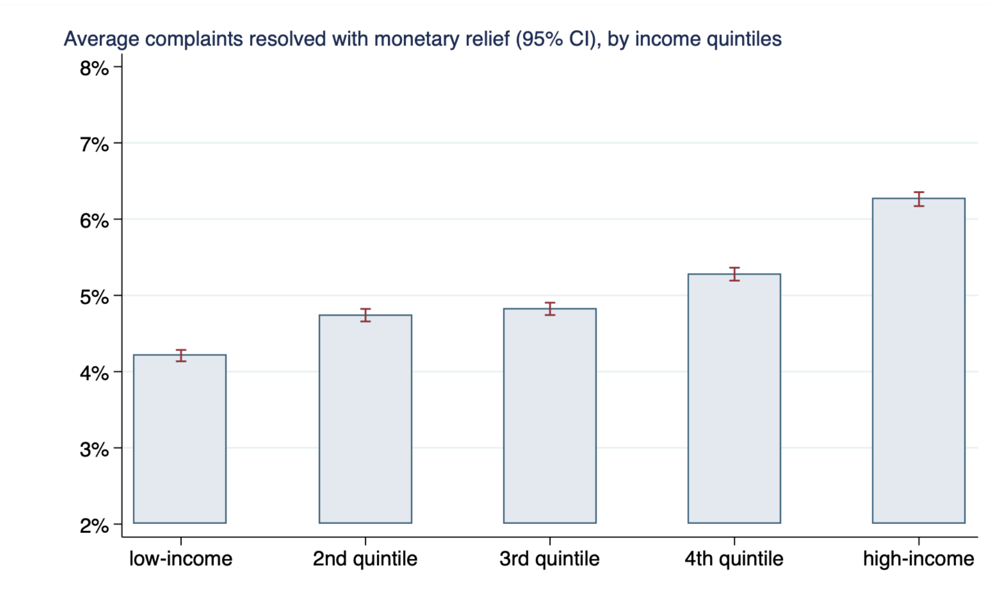


Figure 2: **The Distribution of Financial restitution**

The Figure shows how financial restitution is distributed across different demographic characteristics. Panel A shows monetary relief across quintiles based on complaint's zip code household median income (from low to high). Panel B shows monetary relief across quintiles based on complaint's zip code percentage of Black population (from high to low).

Panel A: Financial Restitution Across Consumer Incomes



Panel B: Financial Restitution Across Consumer Races

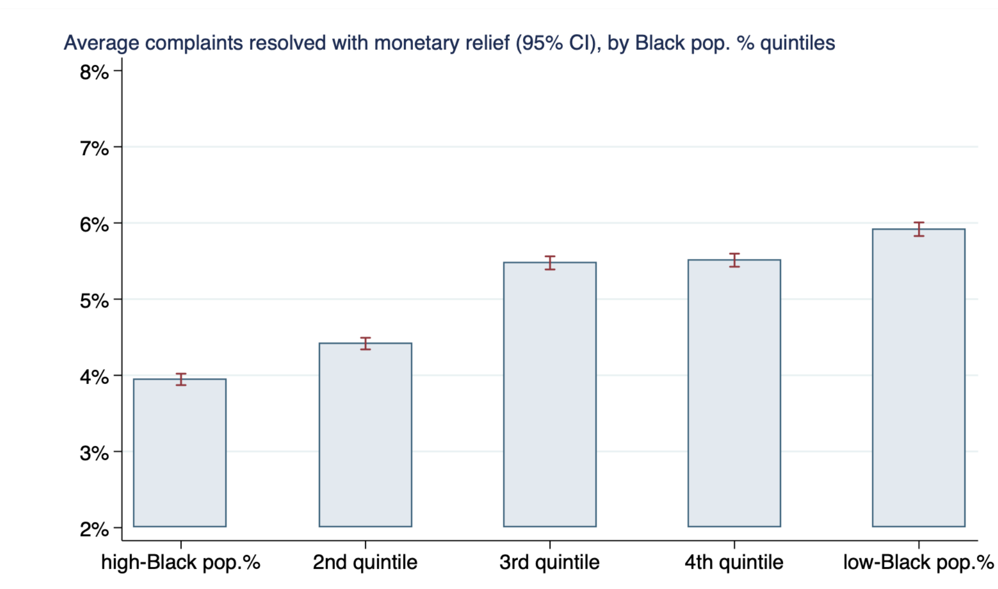
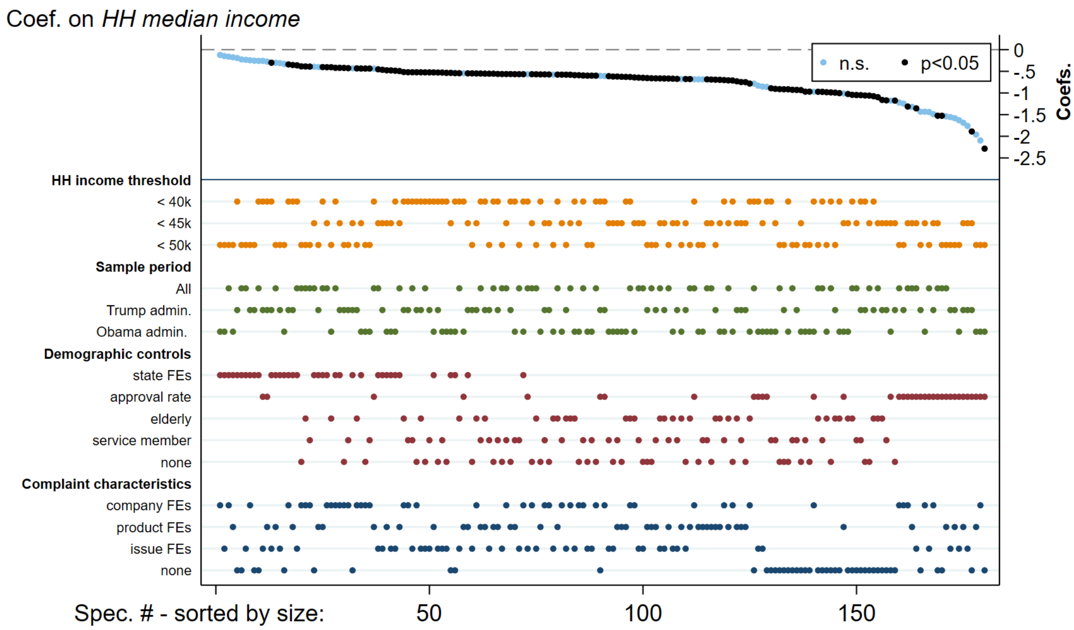


Figure 3: **Robustness of the Financial Restitution Gap**

The Figure shows specification curve analysis outputs for regressions with dependent variable a dummy equal to 1 when the complaint has been solved with monetary relief, 0 otherwise. Panel A focuses on household median income effects on the likelihood of monetary relief. Panel B focuses on Black population percentage effects on the likelihood of monetary relief.

Panel A: Financial Restitution Across Consumer Incomes



Panel B: Financial Restitution Across Consumer Races

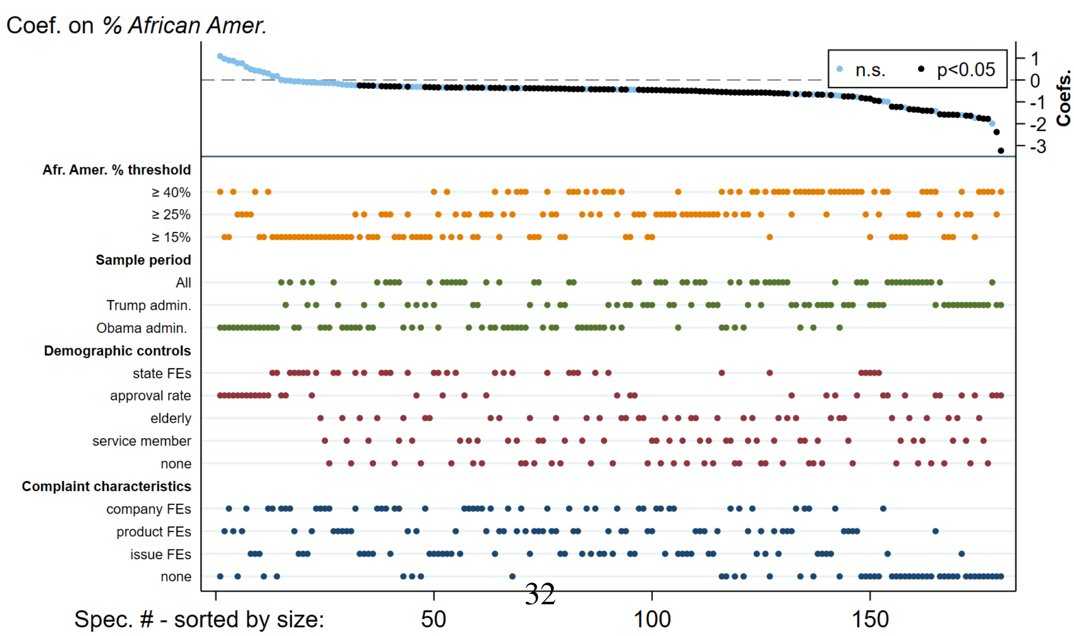
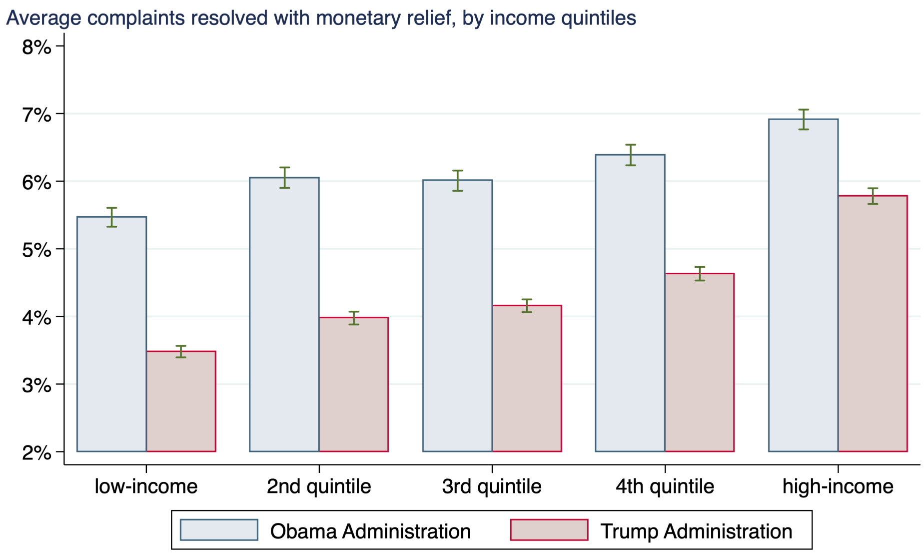


Figure 4: **Financial Restitution Under Different Political Regimes**

The Figure shows differences in financial restitution between the Obama and the Trump administrations. Panel A focuses on quintiles based on complaint's zip code household median income (from low to high). Panel B focuses on quintiles based on complaint's zip code percentage of Black population (from high to low).

Panel A: Financial Restitution Across Consumer Incomes



Panel B: Financial Restitution Across Consumer Races

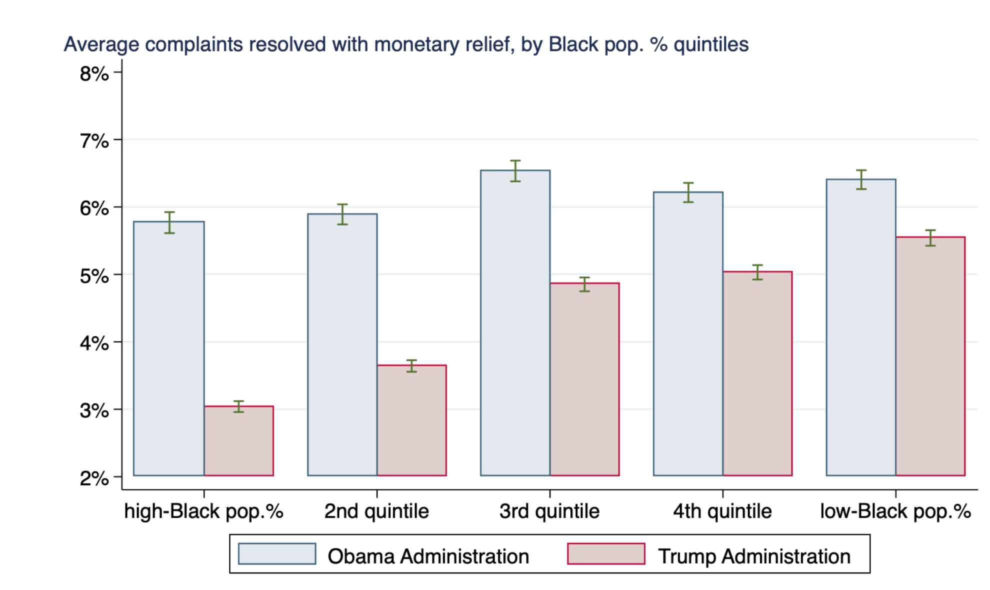
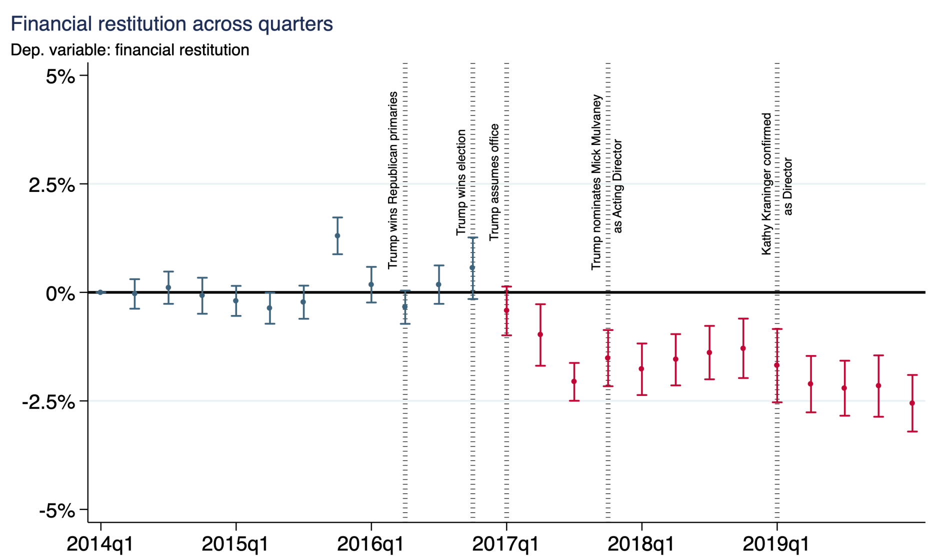


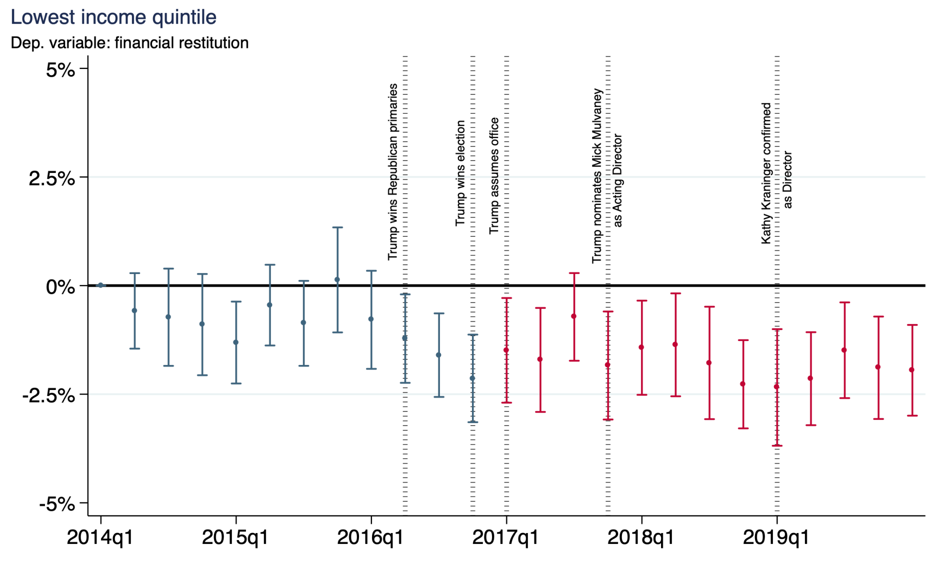
Figure 5: **Financial Restitution Under Different Political Regimes - Event Study**

The Figure shows the evolution of financial restitution over time between the Obama and the Trump administrations. Panel A reports the coefficients of a regression of financial restitution over quarter dummies. Panel B focuses on financial restitution over the lowest quintile based on complaint's zip code household median income. Panel C focuses on financial restitution over the highest quintile based on complaint's zip code percentage of Black population. Across panels, the vertical dotted lines flag relevant Administration/CFPB-related events. Namely, Trump winning the Republican primaries (2016q2), Trump winning the election (2016q4), Trump assuming office (2017q1), Trump appointing Mick Mulvaney as CFPB's Acting Director (2017q4), Trump's nominee Kathy Kraninger being confirmed as CFPB's Director and assuming office (late 2018q4/2019q1).

Panel A: Financial Restitution Over Time



Panel B: Financial Restitution Across Consumer Incomes



Panel C: Financial Restitution Across Consumer Races

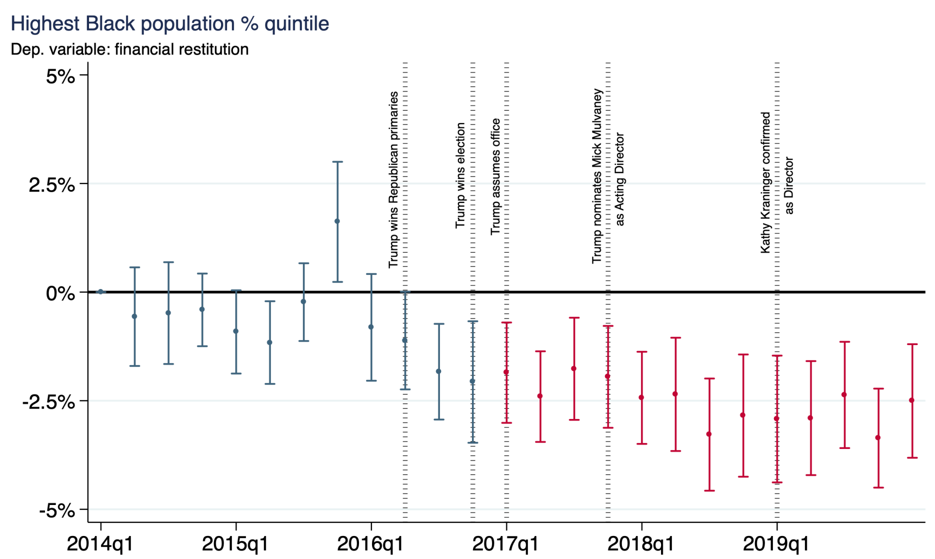


Figure 6: **Financial Restitution Under Different Political Regimes For Different Categories**

The Figure shows how financial restitution patterns have changed across firms from the Obama to the Trump administration. The sample the Figure is based on is a subset of the "Main analysis sample" (Table 1, Panel A) representing all complaints filed between January 2014 and March 2020 and filed with firms that have received at least one complaint during each administration. Firms are categorized by the product they have been complained about the most and the bars represent the percentage of them that have resolved at least one complaint with financial restitution in each administration. Categories are sorted from the highest negative change across administrations to the highest positive change.

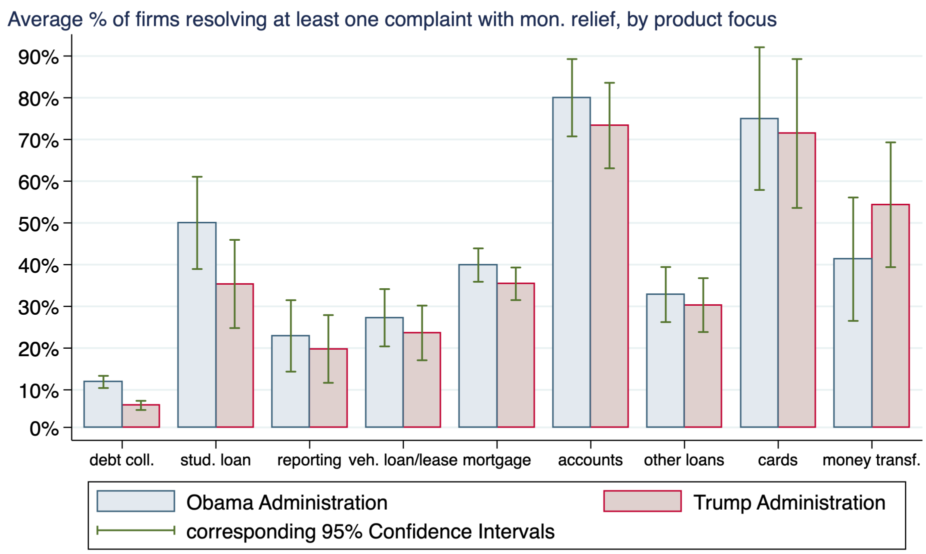
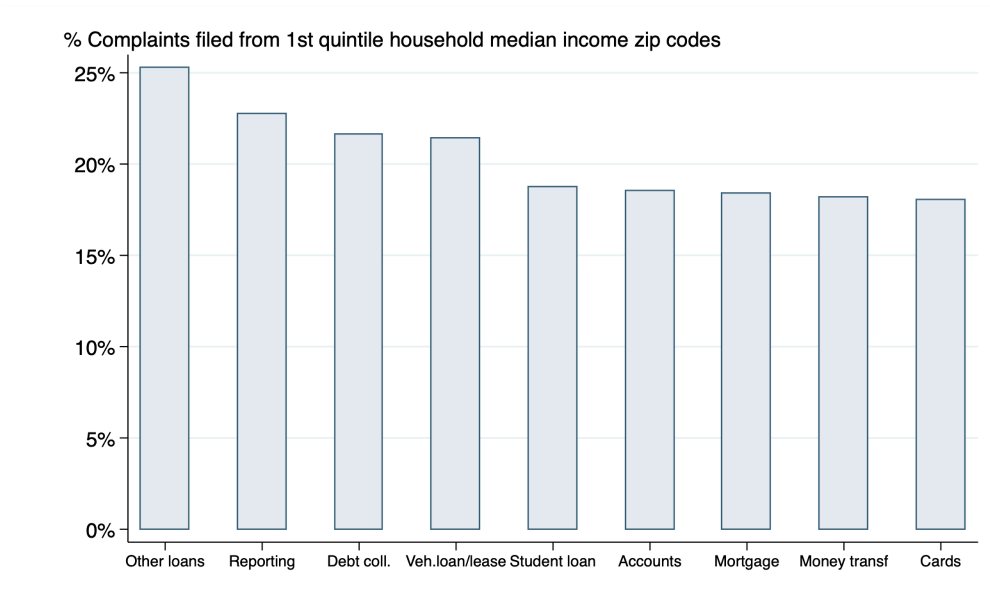


Figure 7: **Complaints For Different Product Categories**

The Figure shows the percentage of complaints across different product categories. Panel A focuses on the lowest income quintile. Panel B focuses on the highest Black population % quintile.

Panel A: Complaints from low-income zip codes



Panel B: Complaints from high-Black population % zip codes

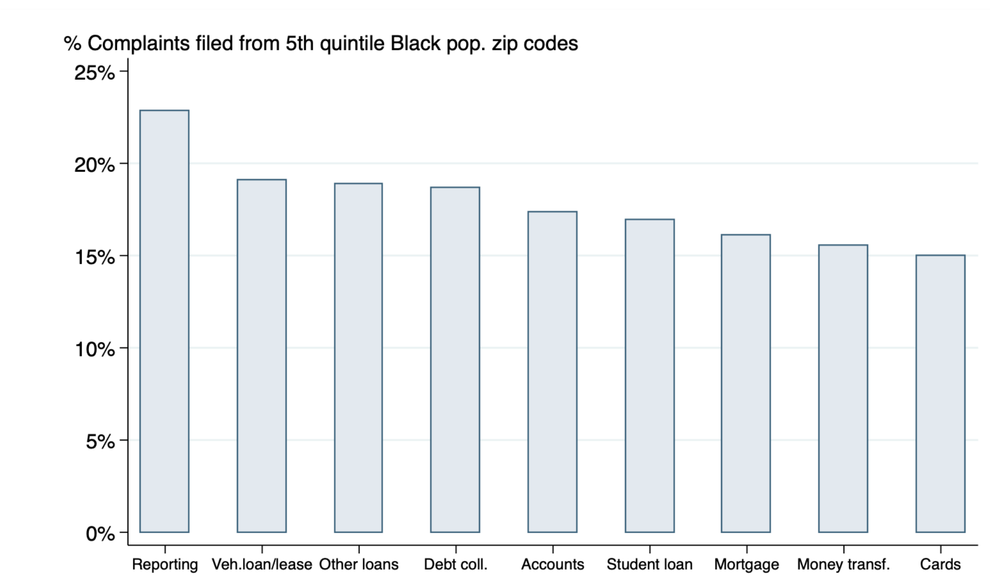
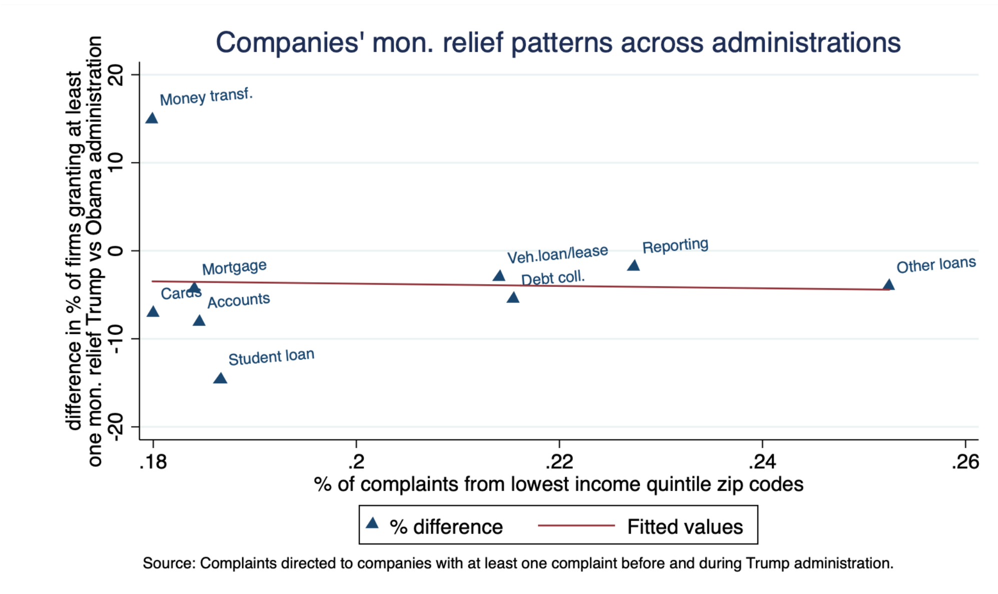


Figure 8: **Financial Restitution Across Product Categories Under Different Political Regimes**

The Figure shows on the y axis the difference in percentages of firms granting at least one monetary relief during the Trump with respect to the Obama administration. Firms are categorized by the product they have been complained about the most. In Panel A, products are further ranked on the x axis according to the percentage of complaints coming from the zip codes with the lowest household median incomes. In Panel B, products are further ranked on the x axis according to the percentage of complaints coming from the zip codes with the highest Black population percentages.

Panel A: Financial Restitution Across Consumer Incomes



Panel B: Financial Restitution Across Consumer Races

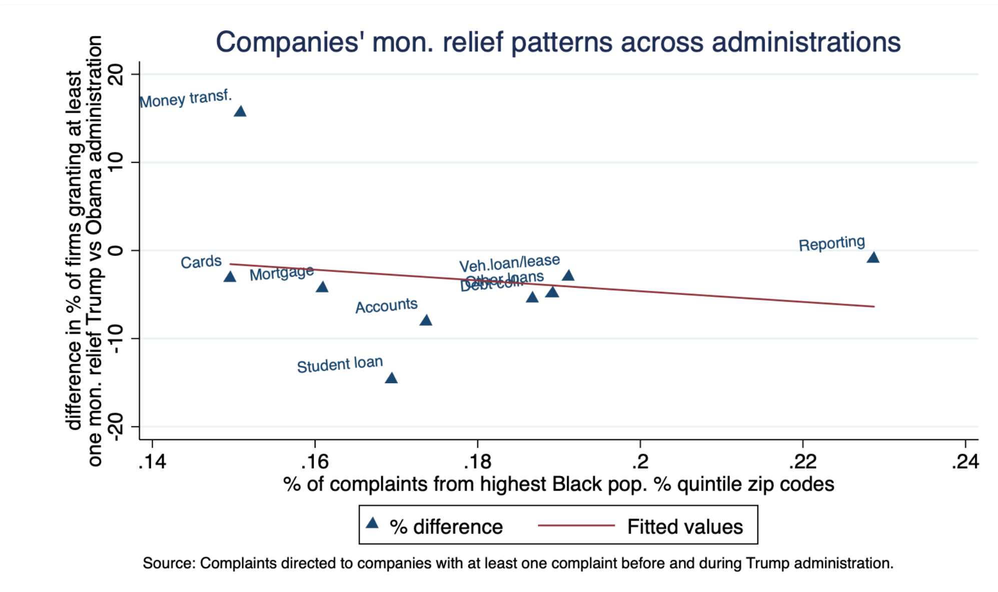
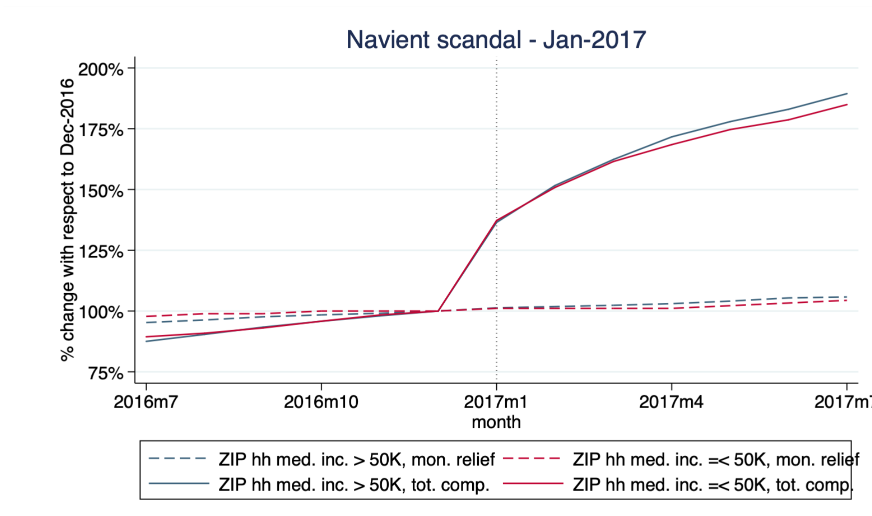


Figure 9: **Financial Restitution and Filings During the Navient Case**

The Figure shows financial restitution and filings patterns during the Navient case of January 2017. The case involved the CFPB in a large settlement. Across panels, solid lines represent percentage differences in complaints filed with respect to complaints filed in December 2016 (one month before the case) and dotted lines represent percentage differences in complaints solved with financial restitution with respect to the complaints solved with financial restitution in December 2016. In Panel A, red lines refer to complaints from zip codes with household median income below \$50,000, blue lines to complaints from zip codes with household median income above \$50,000. In panel B, red lines refer to complaints from zip codes with Black population percentage above 25%, blue lines refer to complaints from zip codes with Black population percentage below 25%.

Panel A: Low income zip codes



Panel B: Black zip codes

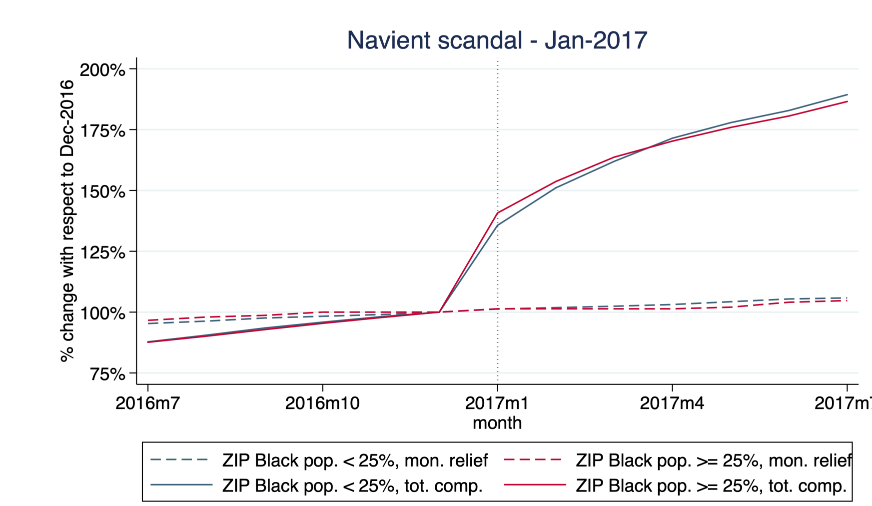
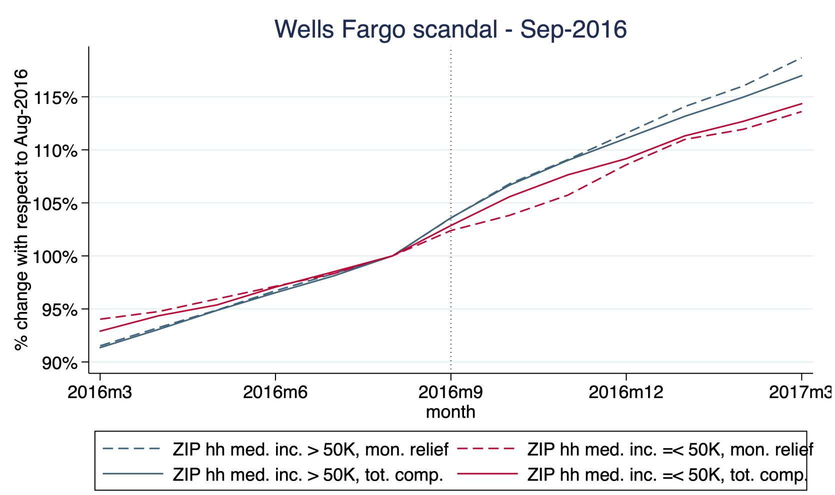


Figure 10: **Financial Restitution and Filings During the Wells Fargo Case**

The Figure shows financial restitution and filings patterns during the Wells Fargo case of September 2016. The case involved the CFPB in a large settlement. Across panels, solid lines represent percentage differences in complaints filed with respect to complaints filed in August 2016 (one month before the case) and dotted lines represent percentage differences in complaints solved with financial restitution with respect to the complaints solved with financial restitution in August 2016. In Panel A, red lines refer to complaints from zip codes with household median income below $50,000, blue lines to complaints from zip codes with household median income above $50,000. In panel B, red lines refer to complaints from zip codes with Black population percentage above 25%, blue lines refer to complaints from zip codes with Black population percentage below 25%.

Panel A: Low income zip codes



Panel B: Black zip codes

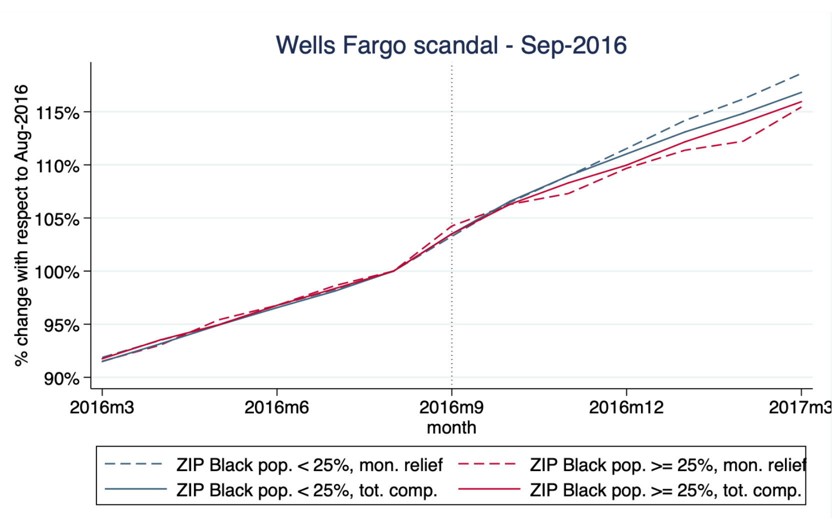


Table 1: **Summary Statistics**

Description: The table presents summary statistics for the samples employed in the analysis. Panel A shows the two different samples. "Main analysis" refers to analysis not involving textual features and its relative sample comprehends the entirety of complaints in the public CFPB database from January 2014 until March 2020 (namely 1,345,485 complaints). "Text analysis" refers to the remainder of the analysis, involving textual features, and its relative sample comprehends the complaints in the public CFPB database with a machine-readable narrative from March 2015 (when the narratives have first been made public) until March 2020. Panel B shows summary statistics for the main continuous variables in the analysis, Demographics drawing from the "Main analysis sample" and Textuals drawing from the "Text analysis sample". Panel C shows "Main analysis sample" splits across different dimensions.

Panel A

	% of CFPB database	# complaints
Main analysis sample	100	1,345,485
Text analysis sample	36.63	492,852

Panel B

variable	mean	std dev	25^{th} %tile	median	75^{th} %tile
Demographics					
Black population %	16.05	12.46	6.63	13.23	21.96
household med. income (thous.)	65.17	15.71	54.92	62.10	72.32
Textuals					
narrative length	148	110	61	116	211
Flesch reading ease score	63.31	41.44	55.22	65.39	74.16
Gunning Fog index	11.31	3.31	9.18	11.13	13.16

Panel C

	% of sample
Complaint resolution	
Closed	0.95
Closed with explanation	80.34
Closed with monetary relief	5.06
Closed with non-monetary relief	13.17
In progress	0.00037
Untimely response	0.49
Products	
Checking or savings account	8.62
Credit card or prepaid card	9.83
Credit reporting, credit repair services, or other reports	36.25
Debt collection	20.30
Money transfer, virtual currency, or money service	1.46
Mortgage	15.35
Payday loan, title loan, or personal loan	2.03
Student loan	3.76
Vehicle loan or lease	2.41
Complaints from zipcodes	
with Black population $>$ 10%	60.32
with Black population $>$ 25%	18.73
with Black population $>$ 50%	2.61
with income $=<$ 65,000	62.94
with income $=<$ 50,000	12.43
with income $=<$ 45,000	4.32
Complaint narrative	
available	38.95
not available	61.05

Table 2: **Baseline regressions on financial restitution**

Description: The table presents whether complaints have a different likelihood of receiving financial restitution across demographic groups. It is based on the "Main analysis sample" illustrated in Table 1 (Panel A). Panel A focuses on complaint's zip code household median income. Panel B focuses on complaint's zip code percentage of Black population. The dependent variable *financial restitution* is a dummy variable equal to 1 if the complaint received financial restitution, 0 otherwise. In panel A, *demographics (income), (Z)* is the standardized household median income of the zip code where the complaint originated. In panel B, *demographics (Black pop.%) (Z)* is the standardized percentage of Black population in the zip code where the complaint originated, entering regressions with a negative sign. Across panels, *approval rate* is the % of mortgages approved in the zip code according to HMDA data. *filer's age > 61* is a dummy variable equal to 1 if the filer has reported being of age 62 or older, 0 otherwise. All standard errors (reported in parenthesis) are clustered at the state level.

Panel A

	financial restitution					
	(1)	(2)	(3)	(4)	(5)	(6)
demographics (income) (Z)	0.00613***	0.00575***	0.00633***	0.00164***	0.00209***	0.00113***
	(0.00098)	(0.00091)	(0.00098)	(0.00042)	(0.00044)	(0.00025)
approval rate		0.0340				0.0266***
		(0.035)				(0.0093)
filer's age > 61			0.0221***			0.00371***
			(0.0016)			(0.00079)
Fixed effects						
year	x	x	x	x	x	x
product				x		x
company					x	x
observations	1,345,478	1,345,478	1,230,494	1,345,478	1,344,313	1,229,356
R-squared	0.0026	0.0027	0.0033	0.12	0.11	0.15

Panel B

	financial restitution					
	(1)	(2)	(3)	(4)	(5)	(6)
demographics (Black pop.%) (Z)	0.00602***	0.00585***	0.00597***	0.00217***	0.00187***	0.00113***
	(0.00099)	(0.0010)	(0.0010)	(0.00032)	(0.00045)	(0.00035)
approval rate		0.00930				0.0222**
		(0.045)				(0.011)
filer's age > 61			0.0211***			0.00352***
			(0.0016)			(0.00080)
Fixed effects						
year	x	x	x	x	x	x
product				x		x
company					x	x
observations	1,345,478	1,345,478	1,230,494	1,345,478	1,344,313	1,229,356
R-squared	0.0026	0.0026	0.0032	0.12	0.11	0.15

Table 3: **Financial restitution across different political regimes**

Description: The table presents whether complaints from low-income, high-Black population zip codes have a different likelihood of receiving financial restitution across administrations. It is based on the "Main analysis sample" illustrated in Table 1 (Panel A). Panel A focuses on complaint's zip code household median income. Panel B focuses on complaint's zip code percentage of Black population. The dependent variable *financial restitution* is a dummy variable equal to 1 if the complaint received financial restitution, 0 otherwise. In panel A, *demographics (income) (Z)* is the standardized household median income of the zip code where the complaint originated. In panel B, *demographics (Black pop.%) (Z)* is the standardized percentage of Black population in the zip code where the complaint originated, entering regressions with a negative sign. Across panels, *approval rate* is the % of mortgages approved in the zip code according to HMDA data. *filer's age > 61* is a dummy variable equal to 1 if the filer has reported being of age 62 or older, 0 otherwise. *Trump adm.* is a dummy variable equal to 1 if the date the CFPB received the complaint is greater than or equal to the 20th of January 2017 (the start of the Trump administration). Across panels, Column 1 is based on complaints submitted during the Obama administration only, Column 2 is based on complaints submitted during the Trump administration only, Columns 3 and 4 span the entire sample. All standard errors (reported in parenthesis) are clustered at the state level.

Panel A

	financial restitution			
	(1)	(2)	(3)	(4)
	Obama adm.	Trump adm.	both	both
demographics (income) (Z)	0.00442***	0.00736***	0.00438***	0.00151**
	(0.00094)	(0.0012)	(0.00085)	(0.00066)
Trump adm.			-0.0150***	-0.00423**
			(0.0034)	(0.0019)
demographics (income) x Trump adm.			0.00276**	0.00101
			(0.0011)	(0.00085)
approval rate			0.0342	
			(0.035)	
filer's age > 61			0.0219***	
			(0.0016)	
Fixed effects				
year	x	x	x	x
company				x
observations	520,226	825,252	1,230,494	1,344,313
R-squared	0.00038	0.0016	0.0035	0.11

Panel B

	financial restitution			
	(1)	(2)	(3)	(4)
	Obama adm.	Trump adm.	both	both
demographics (Black pop.%) (Z)	0.00227**	0.00840***	0.00197*	0.00108
	(0.0011)	(0.0011)	(0.0011)	(0.00077)
Trump adm.			-0.0149***	-0.00424**
			(0.0036)	(0.0019)
demographics (Black pop.%) x Trump adm.			0.00623***	0.00129*
			(0.0012)	(0.00074)
approval rate			0.0128	
			(0.047)	
filer's age > 61			0.0210***	
			(0.0016)	
Fixed effects				
year	x	x	x	x
company				x
observations	520,226	825,252	1,230,494	1,344,313
R-squared	0.00010	0.0020	0.0035	0.11

Table 4: **Firms' Monetary Relief Patterns across administrations**

Description: This table presents coefficients β_3 of regression equation (1) for sub-samples of the "Main analysis sample" (illustrated in Table 1, Panel A) based on firm size and firm monetary relief patterns during the Obama administration. Firm size is proxied by the overall number of complaints received during the Obama administration (different rows). Firm monetary relief patterns include no monetary relief pattern granted during the Obama administration, monetary relief below median and monetary relief above median during the Obama administration (different columns). Coefficients are normalized by the corresponding sub-sample mean of monetary relief percentage. P-values are reported in square brackets. In panel A's regressions, *demographics (income) (Z)* is the standardized household median income of the zip code where the complaint originated. In panel B's regressions, *demographics (Black pop.%) (Z)* is the standardized percentage of Black population in the zip code where the complaint originated, entering regressions with a negative sign. Across tables, the number next each coefficient represents the number of firms entering the corresponding sub-sample. All standard errors (reported in parenthesis) are clustered at the state level.

Panel A - Interaction coefficients for *demographics (Z) (income) x Trump adm.*

	no mon. rel. under Obama		below med. mon. rel. under Obama		above med. mon. rel. under Obama	
(complaints Obama adm.)	$\frac{\beta(demographics\ x\ post\ Trump)}{mon.rel.\ subsample\ mean}$ [p-value]	# firms	$\frac{\beta(demographics\ x\ post\ Trump)}{mon.rel.\ subsample\ mean}$ [p-value]	# firms	$\frac{\beta(demographics\ x\ post\ Trump)}{mon.rel.\ subsample\ mean}$ [p-value]	# firms
$\leq$ 25 complaints	0.3144***	2,593	0.0717	216	0.1352	206
	[0.0016]		[0.96]		[0.14]	
$>$ 25 & $\leq$100 complaints	0.4313	415	-0.2136	92	-0.0949	92
			[0.12]		[0.31]	
$>$ 100 & $\leq$ 1,000 complaints	0.2585	148	0.1864*	74	0.0650*	74
	[0.48]		[0.095]		[0.083]	
$>$ 1,000 complaints	-0.4963	8	-0.0544	25	0.0309**	24
	[0.50]		[0.35]		[0.049]	
all complaints #	0.3105***	3,164	0.0745**	402	0.0273**	401
	[0.0027]		[0.023]		[0.027]	

Panel B - Interaction coefficients for *demographics (Z) (Black pop.%) x Trump adm.*

	no mon. rel. under Obama		below med. mon. rel. under Obama		above med. mon. rel. under Obama	
(complaints Obama adm.)	$\frac{\beta(demographics\ xpost\ Trump)}{mon.rel.\ subsample\ mean}$ [p-value]	# firms	$\frac{\beta(demographics\ xpost\ Trump)}{mon.rel.\ subsample\ mean}$ [p-value]	# firms	$\frac{\beta(demographics\ xpost\ Trump)}{mon.rel.\ subsample\ mean}$ [p-value]	# firms
$\leq$ 25 complaints	0.1990**	2,593	0.0045	216	0.0101	206
	[0.029]		[0.96]		[0.90]	
$>$ 25 & $\leq$100 complaints	-0.1615	415	0.0560	92	-0.0686	92
			[0.67]		[0.32]	
$>$ 100 & $\leq$ 1,000 complaints	0.7016***	148	0.1092	74	0.1251***	74
	[0.0087]		[0.13]		[0.00014]	
$>$ 1,000 complaints	0.5448	8	0.0518	25	0.0492***	24
	[0.19]		[0.34]		[0.0029]	
all complaints #	0.2722***	3,164	0.1340***	402	0.0087**	401
	[0.0012]		[0.0000038]		[0.022]	

Table 5: **Quality of Complaints Narratives**

Description: The table presents whether complaints from low-income, high-Black population zip codes have different quality. It is based on the "Text analysis sample" illustrated in Table 1 (Panel A). Across panels, the first two columns report results where *demographics (Z)* is the standardized household median income of the zip code where the complaint originated. Columns 3 and 4 report results where *demographics (Z)* is the standardized percentage of Black population in the zip code where the complaint originated, entering regressions with a negative sign. *Trump adm.* is a dummy variable equal to 1 if the date the CFPB received the complaint is greater than or equal to the 20th of January 2017 (the start of the Trump administration). Panel A reports results for the dependent variable *narrative length*, capturing the number of words used in each complaint. Panel B reports results for the dependent variable *Flesch reading ease score* and Panel C for *Gunning Fox index*. The latter enters regressions with a negative sign to ensure that higher values of both indexes capture an easier to read complaint. Please refer to Section 4.2 for a detailed explanation of the indexes' computation. All standard errors (reported in parenthesis) are clustered at the state level.

Panel A

	(1)	(2)	(3)	(4)
	demographics (income)	demographics (income)	demographics (Black pop.%)	demographics (Black pop.%)
	narrative length			
demographics (Z)	0.340	0.384	0.568	-0.446
	(0.80)	(0.53)	(0.55)	(0.66)
Trump adm.		10.51***		10.45***
		(1.55)		(1.60)
demographics x Trump adm.		-0.0586		1.344**
		(0.84)		(0.63)
constant	148.0***	140.3***	148.0***	140.4***
	(1.12)	(1.56)	(1.12)	(1.55)
Fixed effects				
year	x	x	x	x
product	x	x	x	x
issue	x	x	x	x
observations	492,849	492,849	492,849	492,849
R-squared	0.078	0.078	0.078	0.078

Panel B

	(1)	(2)	(3)	(4)
	demographics (income)	demographics (income)	demographic (Black pop.%)	demographics (Black pop.%)
		Flesch reading ease score		
demographics (Z)	-0.251*	-0.411***	0.458**	0.303*
	(0.15)	(0.10)	(0.18)	(0.17)
Trump adm.		0.628		0.619
		(0.47)		(0.48)
demographics x Trump adm.		0.221*		0.207
		(0.12)		(0.22)
constant	63.31***	62.85***	63.31***	62.86***
	(0.19)	(0.39)	(0.21)	(0.39)
observations	492,849	492,849	492,849	492,849
R-squared	0.013	0.013	0.013	0.013
		Gunning Fog index		
demographics (Z)	-0.0409	-0.0675***	0.0541*	0.0521
	(0.025)	(0.020)	(0.031)	(0.034)
Trump adm.		0.0381		0.0381
		(0.078)		(0.079)
demographics x Trump adm.		0.0368**		0.00267
		(0.016)		(0.031)
constant	-11.31***	-11.34***	-11.31***	-11.34***
	(0.039)	(0.069)	(0.041)	(0.070)
observations	492,849	492,849	492,849	492,849
R-squared	0.050	0.050	0.050	0.050
Fixed effects				
year	x	x	x	x
product	x	x	x	x
issue	x	x	x	x

Table 6: **Content of Complaints Narratives**

Description: The table presents whether complaints from different demographic groups claim refund or fraud more often. It is based on the "Text analysis sample" illustrated in Table 1 (Panel A). Across panels, the first two columns report results where *demographics (Z)* is the standardized household median income of the zip code where the complaint originated. Columns 3 and 4 report results where *demographics (Z)* is the standardized percentage of Black population in the zip code where the complaint originated, entering regressions with a negative sign. *Trump adm.* is a dummy variable equal to 1 if the date the CFPB received the complaint is greater than or equal to the 20th of January 2017 (the start of the Trump administration). Panel A reports results for the dependent variables *"refund" mentions* and *broad mentions of refund*. The former is a dummy equal to 1 if the word "refund" is mentioned at least once in the complaint, 0 otherwise. The latter is a dummy equal to 1 if the complaint explicitly mentions at least one of the following words: "refund", "refunding", "refunded", "refunds", "repay", "reimburse", "reimbursement", "reimbursements", "reimbursing", "reimbursed", "repayment", "repayments", "repaying", "pay back", "paying back", "paid back", "make good", "making good", "made good", "compensate", "compensation", "compensations", "compensating", "compensated", "recoup", "recoups", "recouping", "recouped", "remunerate", "remuneration", "remunerations", "remunerating", "remunerated", "squaring accounts with", "squared accounts with", "square accounts with". Panel B reports results for the dependent variables *"fraud" mentions* and *broad mentions of fraud*. The former is a dummy equal to 1 if the word "fraud" is mentioned at least once in the complaint, 0 otherwise. The latter is a dummy equal to 1 if the complaint explicitly mentions at least one of the following words: "fraud", "deceit", "deception", "trickery", "rip-off", "fake", "con", "impostor", "fraudster", "deceive", "deceiving", "deceived", "defraud", "defrauded", "cheat", "cheating", "cheated", "trick", "tricked", "tricking", "mislead", "misled", "misleading", "misguide", "misguided", "misguiding". All standard errors (reported in parenthesis) are clustered at the state level.

Panel A

	(1)	(2)	(3)	(4)
	demographics (income)	demographics (income)	demographics (Black pop.%)	demographics (Black pop.%)
		"refund" mentions		
demographics (Z)	0.00127***	0.000591	0.000556	-0.000279
	(0.00042)	(0.00060)	(0.00042)	(0.00058)
Trump adm.		0.000535		0.000480
		(0.0028)		(0.0028)
demographics x Trump adm.		0.000944		0.00111**
		(0.00070)		(0.00051)
constant	0.0357***	0.0353***	0.0357***	0.0354***
	(0.00044)	(0.0019)	(0.00048)	(0.0018)
observations	492,849	492,849	492,849	492,849
R-squared	0.067	0.067	0.067	0.067
		broad mentions of refund		
demographics (Z)	0.00213***	0.000284	0.00124	0.000232
	(0.00039)	(0.00064)	(0.00076)	(0.00094)
Trump adm.		-0.00233		-0.00240
		(0.0038)		(0.0038)
demographics x Trump adm.		0.00256***		0.00134*
		(0.00085)		(0.00071)
constant	0.0692***	0.0710***	0.0692***	0.0710***
	(0.00068)	(0.0028)	(0.00074)	(0.0027)
observations	492,849	492,849	492,849	492,849
R-squared	0.090	0.090	0.090	0.090
Fixed effects				
year	x	x	x	x
product	x	x	x	x
issue	x	x	x	x

Panel B

	(1)	(2)	(3)	(4)
	demographics (income)	demographics (income)	demographics (Black pop.%)	demographics (Black pop.%)
		"fraud" mentions		
demographics (Z)	0.000249	0.000280	-0.00137	-0.00143
	(0.00077)	(0.00094)	(0.0011)	(0.0011)
Trump adm.		0.00597**		0.00600**
		(0.0030)		(0.0029)
demographics x Trump adm.		-0.0000409		0.0000810
		(0.00100)		(0.00096)
constant	0.0700***	0.0656***	0.0700***	0.0656***
	(0.0012)	(0.0027)	(0.0013)	(0.0027)
observations	492,849	492,849	492,849	492,849
R-squared	0.045	0.045	0.045	0.045
		broad mentions of fraud		
demographics (Z)	0.00217	0.00750**	-0.00434	-0.00403
	(0.0031)	(0.0029)	(0.0028)	(0.0030)
Trump adm.		0.0210*		0.0209*
		(0.011)		(0.011)
demographics x Trump adm.		-0.00738**		-0.000411
		(0.0033)		(0.0029)
constant	0.573***	0.558***	0.573***	0.558***
	(0.0040)	(0.0095)	(0.0039)	(0.0086)
observations	492,849	492,849	492,849	492,849
R-squared	0.014	0.014	0.014	0.014
Fixed effects				
year	x	x	x	x
product	x	x	x	x
issue	x	x	x	x

Appendix to:

The Financial Restitution Gap in Consumer Finance: Lessons from Filings to the CFPB

(intended for online publication)

A.I On Filing Rates

Our results show that there are differences in the propensity to receive financial restitution across demographics groups. The analysis is conditional on a consumer submitting a complaint. Differences in the quality of complaints might be one reason why there are differences in the propensity to receive financial restitution. Section 4.2 makes progress toward addressing possible differences in the quality of complaints by using textual analysis to examine differences in the written descriptions of the complaints. However, such analysis leaves open the possibility of additional omitted factors that our data does not include.

This section explores whether there are differences in complaint filing rates. Multiple channels would determine filing rates. (A) The propensity for consumers to be victims of unfair business practices such as fraud. (B) Consumersâ beliefs that filing a complaints is worth their time and will resolve in their favor. To the latter, beliefs would form following both (i) actual unfair business practice that the consumer accurately perceives and (ii) fair business practices that the consumer misperceives as being unfair. Unfortunately, we can only observe topline filing rates and cannot disentangle the contribution of each factor. For example, wealthier individuals might be targets of fraud because of the large potential gains. On the other hand, low-income individuals might be targets of fraud because they are easier victims (they might have less scope for recourse or less formal training in personal finances).

Low-income complaints might be less likely to receive financial restitution because low-income consumers are more likely to file complaints about fair business practices. However, as described above, we are unable to determine whether complaints are about fair or unfair practices. We can only observe topline filing rates. To this end, we examine differences in filing rates with the caveat that the results are informative only under the assumption that consumers across the demographic distribution are equally likely to be targets of unfair business practices. Moreover, recall that the differences in financial restitution across demographic groups emerge under different political administrations. We would also have to observe differences in filing rates that change over time.

The following analysis explores filing rates across the demographic distribution. To summarize our findings, we observe a U-shaped pattern where both the highest and lowest income, Black population percentage quintiles are more likely to file complaints with the CFPB. We also observe that there is a larger increase in the filing rates originating from low-income and high-Black population percentage areas occurring during the Trump administration. Though this might explain the change in financial restitution across different political administrations, we find that the response to the Equifax data breach in 2017 explains the change in filing rates, but not the change in financial restitution. The increase in filing rates starting in 2017 is isolated to credit reporting, is directed toward the major credit bureaus, and comes mostly from low-income and high-Black population percentage areas. Furthermore, our main results on differences in financial restitution across demographic groups hold after we exclude credit reporting from the analysis.

A.I.1 Analysis of filing rates

We start by lining up all U.S. zip codes - independently of whether they ever originated a complaint and when they did so - from the lowest household median income to the highest one, and from the highest Black population percentage to the lowest one. We then divide these zip codes into quintiles based on such distributions. We compute quintile filing rates as the amount of complaints filed in each quarter across the zip codes in the quintile over the sum of their population. Note that we line up zip codes and operate zip-code level population calculations based on linked data from the Census at county level, hence the resulting rates are likely to be lower than in reality. We scale them to a population of 10,000 individuals for better readability and remind the reader that they are downsized by construction.

Figure A.I.1: **Filing Rates**

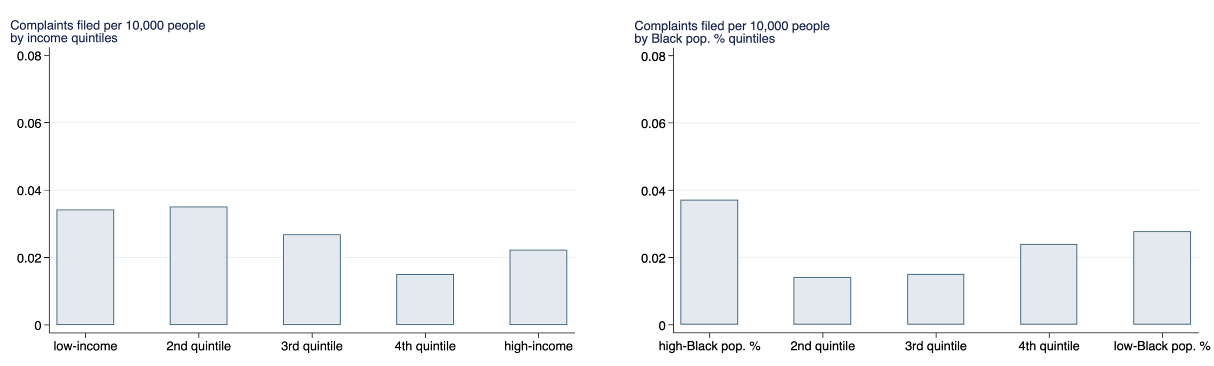
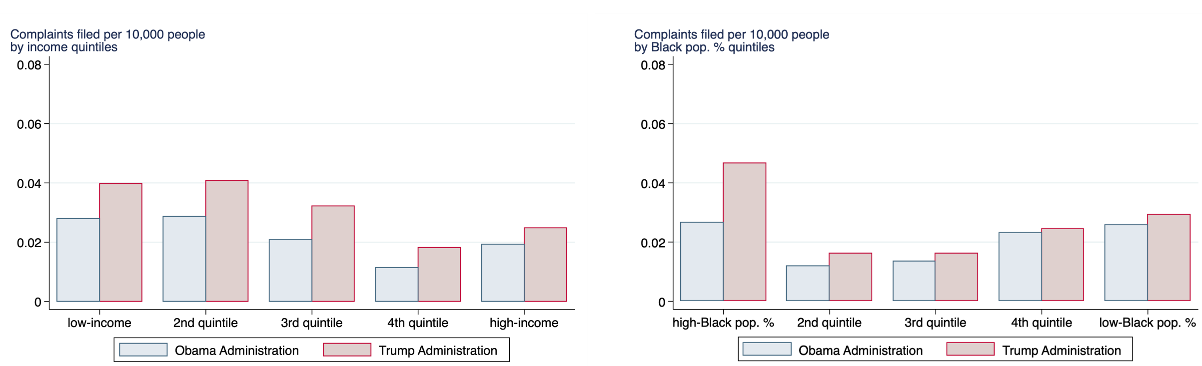


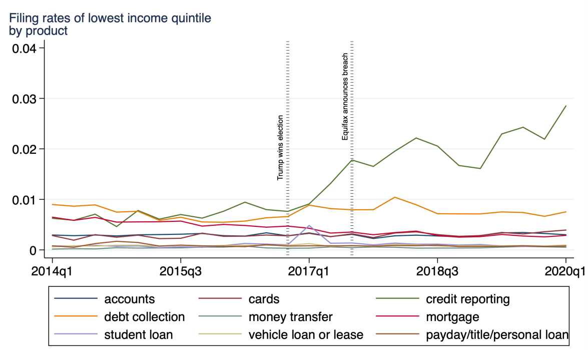
Figure A.I.1 presents said filing rates across quintiles based on household median income (left-hand side panel throughout, from lowest to highest income) and Black population percentage (right-hand side panel throughout, from highest to lowest Black population percentage) computed across quarters and averaged across the entire time-span of our sample. The filing rates are U-shaped across both demographic distributions: both high- and low-quintiles are more likely to file complaints.

Figure A.I.2: **Filing Rates Across Administrations**



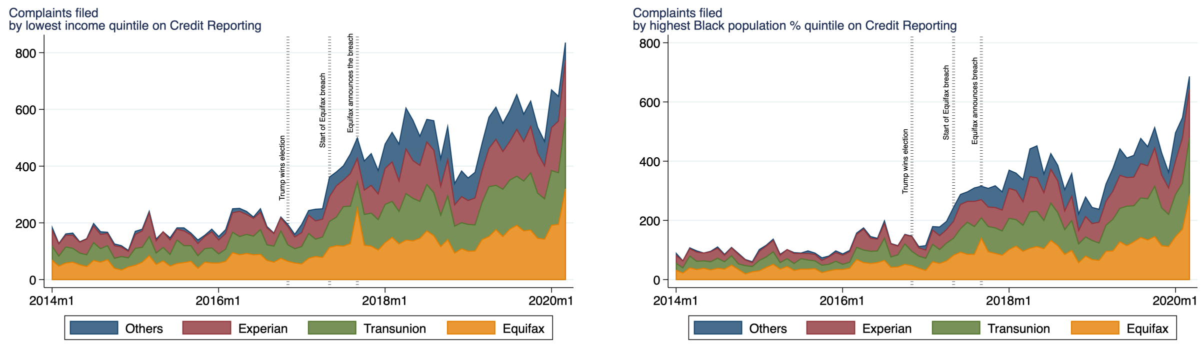
Next, we examine how filing rates changed across Presidential administrations in Figure A.I.2 above. While there has been an increase in the filing rate during the Trump administration virtually across all demographic quintiles, the increase appears sharper for the highest Black percentage population quintile and, to a lesser but more spread extent, the low income ones. Because this increase might explain the changes in financial restitution, we proceed to investigate their precise timing and further distinguish across financial products. Figure A.I.3 below follows the evolution of the filing rate in the lowest demographic quintiles for each product over the quarters in our sample.

Figure A.I.3: **Lowest-income, highest-Black pop. % Filing Rates**



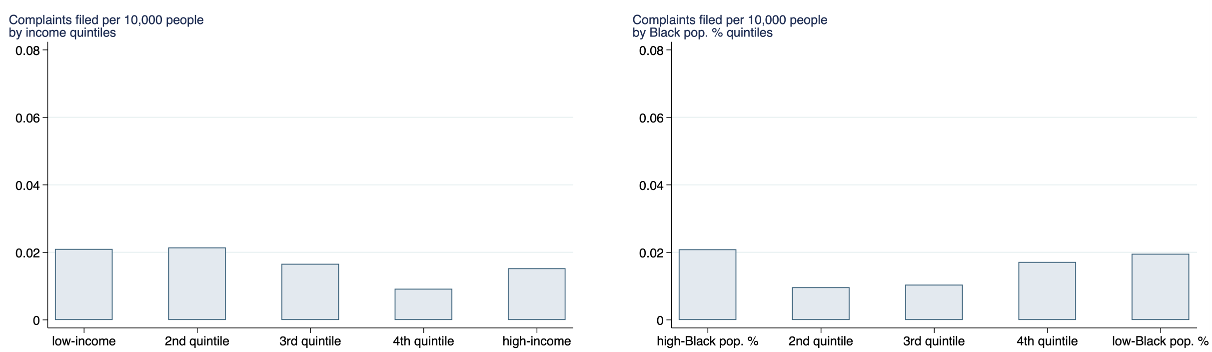
The increase in filing rates over time can mainly be attributed to complaints about credit reporting. The increase began in 2017 and continues to today. The first local peak was in September 2017 in line with the beginning of public reporting on the Equifax scandal. Equifax experienced a data breach that began in May 2017, but was publicly announced only in September. The CFPB has achieved settlement with Equifax on the matter only recently, on July 22, 2019. Furthermore, the CFPB encouraged individuals to check eligibility for potential reimbursement or free reporting for an extended amount of time. From anecdotal evidence present in the complaint narratives, it appears that low-income and Black individuals became more aware of identity theft and inconsistencies in their credit reports when dealing with multiple agencies during this time-period. Figure A.I.4 below further supports how credit reporting complaints started rising in May 2017.

Figure A.I.4: **Lowest-income, highest-Black pop. % Complaints - Credit Reporting**



In light of these patterns, we repeat our analysis of filing rates and financial restitution excluding complaints on credit reporting as a potentially confounding element. Figure A.I.5 below replicates filing rates as in Figure A.I.1, excluding such complaints.

Figure A.I.5: **Filing Rates without Credit Reporting**



Patterns across the different demographic groups remain the same, despite lower overall levels. We then analyze filing rates and financial restitution evolution across administrations to make sure the results observed in the paper are not influenced by higher filing rates from low-income and Black individuals during the Trump administration.

Figure A.I.6: **Filing Rates Across Administrations without Credit Reporting**

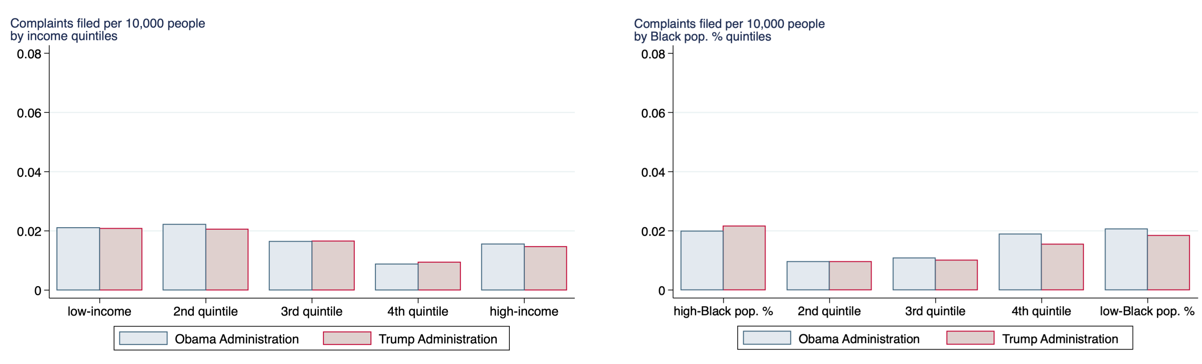
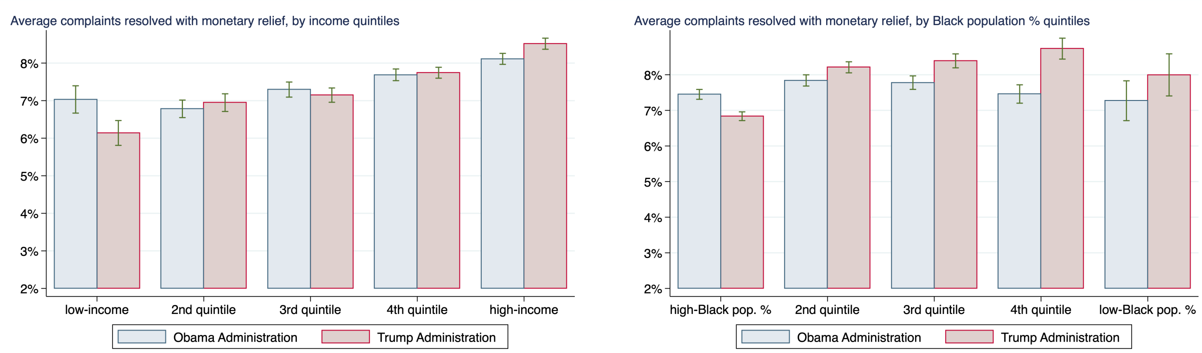


Figure A.I.6 above reports average quarterly filing rates excluding credit reporting complaints across administrations. Interestingly, we do not witness any change in filing rates across administration within each demographic quintile. To ultimately check that the results presented in the paper are not driven by the highlighted credit reporting patterns, we also replicate financial restitution results excluding credit reporting in Figure A.I.7 below.

Figure A.I.7: **Financial Restitution Rates Across Administrations without Credit Reporting**

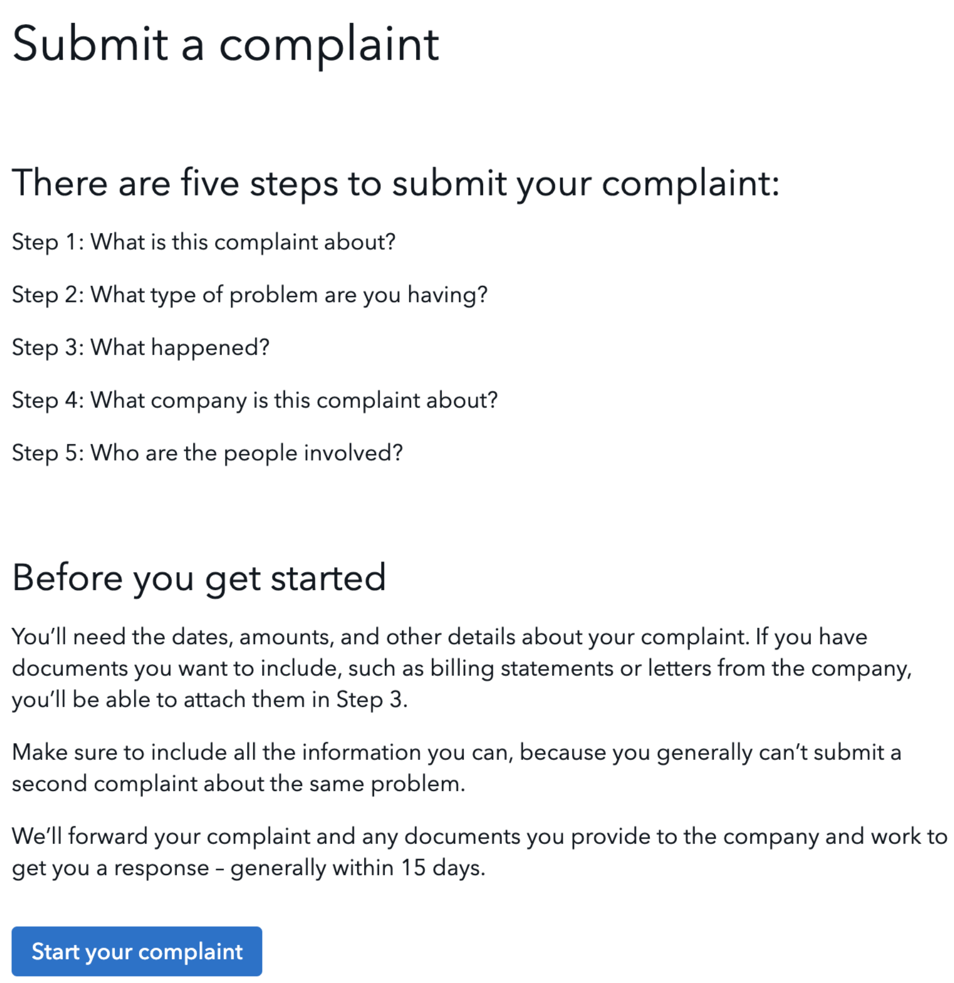


Whereas overall financial restitution levels appear now higher due to the relatively lower occurrence of restitution in credit reporting issues, there is still a clear pattern of disproportionate impact across demographic groups. Low-income and Black individuals appear to receive significantly less financial restitution during the Trump administration relative to the Obama administration, whereas high-income, non-Black individuals receive more. Notably, the change in financial restitution occurred even though the filing rate excluding credit reporting remained constant across administrations. These findings reinforce our interpretation of the results presented in the paper.

A.II Submitting a Complaint on the CFPB Website

Figure A.II.1: **Filing a complaint on the CFPB website**

The Figure shows the different steps for filing a complaint regarding a checking account.



Submit a complaint

There are five steps to submit your complaint:

Step 1: What is this complaint about?

Step 2: What type of problem are you having?

Step 3: What happened?

Step 4: What company is this complaint about?

Step 5: Who are the people involved?

Before you get started

You'll need the dates, amounts, and other details about your complaint. If you have documents you want to include, such as billing statements or letters from the company, you'll be able to attach them in Step 3.

Make sure to include all the information you can, because you generally can't submit a second complaint about the same problem.

We'll forward your complaint and any documents you provide to the company and work to get you a response – generally within 15 days.

Start your complaint

Submit a complaint

What is this complaint about?

Choose the product or service that best matches your complaint.

- ◯ Debt collection
- ◯ Credit reporting, credit repair services, or other personal consumer reports
- ◯ Mortgage
- ◯ Credit card or prepaid card
- ◯ Checking or savings account
- ◯ Vehicle loan or lease
- ◯ Student loan
- ◯ Payday loan, title loan, or personal loan (installment loan or personal line of credit)
- ◯ Money transfer, virtual currency, or money service (check cashing service, currency exchange, cashier's/traveler's check, debt settlement)

Previous | Step 1 of 5 | Next

What type of problem are you having?

Most of the **checking account** complaints we get are about one of the following topics. Select the one that best describes your complaint. You will have the chance to explain your complaint in detail in the next step.

- ◯ Opening an account
- ◯ Managing an account
  (deposits, withdrawals, using ATM card, making or receiving payments, cashing a check, fees)
- ◯ Closing an account
- ◯ Problem caused by your funds being low
- ◯ Problem with a lender or other company charging your account
- ◯ Problem with credit report or credit score

Previous | Step 2 of 5 | Next

What happened?

Describe what happened, and we'll send your comments to the companies involved.

- Include dates, amounts, and actions that were taken by you or the company.
- Do not include personal information, such as your name, account number, address, Social Security number, etc. We may ask for some of this information later, to help the company identify you and your account.

☐ I want the CFPB to publish this description on consumerfinance.gov so that others can learn from my experience. The CFPB will take steps to remove my personal information from this description but someone may still be able to identify me. Learn how it works. I consent to publishing this description after the CFPB has taken these steps.

Publishing this description will not affect how the CFPB handles your complaint.

What would be a fair resolution to this issue?

We'll forward this to the companies involved. Be specific so they know what resolution you are looking for. The company may or may not offer to resolve your complaint.

Attach documents (optional)

Include copies or photos of documents related to your issue, such as contracts, letters, and receipts, and we will forward all materials to the company for review.

Select a file to attach

We accept all file formats, except .dll, .dmg, .exe and .msi, up to 10 MB per file. All uploaded files will be scanned for viruses and will be immediately deleted if one is detected.

Select a file to upload

Previous Step 3 of 5 Next

What company is this complaint about?

We'll forward your entire complaint to the company and request they respond within 15 days of receiving it.

Bank or credit union

Company name

Company name

We will forward your complaint to this company and ask for a response.

We need this information to help the company find you in their system and respond to your complaint. (optional)

- [ ] Account number
  This number is on your billing statement
- [ ] Billing address

Previous | Step 4 of 5 | Next

Who are the people involved?

Identify who is involved in this complaint. This could include:

- "Just you" if you are the account holder or borrower
- "You and someone else" if you are submitting for yourself and want to include another account holder or co-borrower
- "Someone else" if you are submitting for someone else as an authorized third party, such as a lawyer, advocate, or power of attorney

○ Just you

○ You and someone else

○ Someone else

Previous | Step 5 of 5 | Review

Table A.1: **Example of Complaint**

Description: The table presents a complaint from the CFPB database, available at the CFPB database webpage. For an explanation of the information attached to each complaint, refer to the CFPB database fields webpage

.

	Complaint information
Date received	1/17/19
Product	Mortgage
Subproduct	Conventional home mortgage
Issue	Trouble during payment process
Subissue	[blank]
Company	Ditech Financial LLC
State	TX
Zip code	781XX
Company response	Closed with explanation
Complaint narrative	I have been trying to get my Private Mortgage Insurance Removed from my mortgage since XX/XX/XXXX when my mortgage dropped below 80 % loan to value. Last year my mortgage was sold from XXXX XXXX (Under mortgage XXXX) to Ditech Mortgage (account XXXX). I reached out to Ditech via a email (after being told to do so via phone representative) request to remove my PMI on mortgage on XX/XX/XXXX and received no response at all from them, I even checked my junk box and nothing was there. My mortgage papers that I signed state an " Automatic Termination of PMI " that states once my loan is below 78 % loan to value PMI will automatically terminate (I have attached this document). I reached out again today on XX/XX/XXXX to make this request via phone and was told initially to send the request that I already sent it too. I asked to speak with a supervisor and after being put on hold for about 30 minutes, I finally spoke to one. They told me that my loan to value must be under 70 % loan to value and that was their policy. After reading this document to the supervisor, I was told that " they don't have that document on file ". She (XXXX XXXX) sent me a link to send her the form I have. I did so and just told me that I'll be hearing from them in 7-10 business days. Given their past history, I highly doubt that I will hear from them. I did mention to the supervisor and ask her why they weren't staying compliant to the homeowners protection act and she said nothing. From my understand this act requires mortgage companies to drop off PMI once loans are below 78 % LTV and the loan is current. I qualify for both of those items and don't understand why this is such a difficult task.

Figure A.II.2: **Complaints' content**

The Figure shows a wordcloud based on a randomly sampled 10% of the complaint narratives available.