The Decline of Branch Banking*

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Abstract

We study U.S. bank branch openings and closings from 2001 to 2023. Both are concentrated in areas where depositors are more sensitive to interest rates, a pattern driven by financially sophisticated households with greater adoption of digital banking. The effects are strongest for large banks, with lending playing at most a minimal role. Incumbents retain branches where depositors are less rate-sensitive and thus more profitable; entrants avoid such markets because sticky customers are difficult to attract. The COVID-19 pandemic accelerated closures by increasing digital reliance. Overall, our findings underscore depositor rate sensitivity and technology adoption as the primary forces shaping modern branch restructuring.

Keywords: deposit franchise, branch closure, digital banking

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Introduction

This paper examines the drivers of bank branch opening and closure decisions during the recent period of industry restructuring. We show that measures of local financial sophistication strongly predict both outcomes, as depositors in these areas are rate-sensitive and tech-savvy, and as a result, lower deposit franchise value. The findings highlight the different incentives facing incumbent banks versus potential entrants. Incumbents are more likely to close branches in areas with rate-sensitive customers, from whom they have limited ability to extract rents and whom they can increasingly serve without physical branches. In contrast, potential entrants are less likely to open branches in areas with rate-insensitive depositors, as such customers are difficult to attract away from incumbent institutions despite their profitability.

Bank branches grew in aggregate until 2010, with the rate of branch openings exceeding that of closings by a factor of two to three. This net branch growth occurred even as the banking system consolidated. Total branches and offices, however, peaked in 2010 and then began to decline. The rate of decline accelerated around 2015 and further intensified following the COVID-19 pandemic (Figure 1). These recent patterns stand in sharp contrast to the earlier period, when openings consistently outpaced closings (Figure 1, Panel B). Before the Global Financial Crisis (GFC), a forty-year period of banking-industry restructuring unfolded as large banks expanded into new markets by acquiring smaller incumbent banks and by opening new branches. This expansion was fostered by the deregulation of restrictions on branching and interstate banking (Schneider, Strahan, and Yang (2025)). This restructuring sharply reduced the number of banks (due to M&A), but not the number of branches. The purpose of this first wave of M&A was fundamentally to extend large banks' physical reach (Kroszner and Strahan (2014)). By contrast, restructuring since 2010 has reduced both the number of banks and the number of branches.

We argue that technology is the primary driver of branch restructuring today. Internet and mobile banking allow customers to access deposits without physical proximity and make it easier to move funds in response to shocks (as in the SVB episode) or to changes in market interest rates. These advances diminish the role of dense branch networks, making it more efficient for banks to reduce costs by closing less essential locations, even though some branches continue to be opened. Although technology broadly pressures banks to shrink their physical footprint, our empirical strategy focuses on the fact that financially sophisticated customers adopt these technologies more quickly, which helps explain why some branches close earlier than others. This recent wave of restructuring contrasts with the earlier era, when deregulation was the dominant force. Our paper thus explains the contemporary decline in U.S. branch networks and contributes to understanding the broader restructuring of the banking industry.

A central empirical challenge is constructing measures that capture depositor behavior and lending conditions at the branch level for incumbent banks (i.e., those deciding which branches to close). To capture depositor behavior, we construct a measure of interest-rate sensitivity (the Deposit-β). As shown in Drechsler, Savov, and Schnabl (2017), this measure provides a sufficient statistic for local market power, reflecting not only market concentration but also depositors' financial sophistication, attentiveness, and willingness to switch banks. We extend their concept by first estimating bank-level sensitivity from the demographics of the areas in which the bank operates, and then mapping those demographics to individual branches to generate branch-level predictions of β. This approach allows us to recover heterogeneity in depositor rate sensitivity across locations within the same bank and thereby assess how differences in depositor behavior shape branch restructuring decisions. Put differently, our regression models exploit within-bank variation in depositor sensitivity while absorbing overall bank- and time-level factors with fixed effects. Local lending conditions, by contrast, are accounted for using county-level variables or absorbed through *county* $\times$ *year* fixed effects.

For potential entrants, we construct a set of candidate zip codes for each bank. This set includes all zip codes within CBSAs where the bank already operates at least one branch, as well as those in CBSAs where it subsequently opens a new branch. As in the closure analysis, we examine opening decisions within bank-year. For each candidate zip code, we assign the same Deposit-β measure described above, which in this context reflects the expected price sensitivity of depositors if the bank were to enter by opening a new branch. Thus, while incumbents face realized depositor behavior at existing branches, entrants base their decisions on expected depositor sensitivity in potential markets.

To capture depositor behavior, Deposit-β is implemented through this indirect approach, since branch-level measures of deposit sensitivity are not directly available. Recent studies have used deposit quotes from RateWatch, but these data cover only a subset of "rate-setting" branches and do not capture the underlying deposit mix. As a result, they provide little insight into how depositors actually reallocate funds across products—for example, shifting balances from checking to time deposits when the spread is large. Moreover, as emphasized by Begenau and Stafford (2023), many large banks follow uniform pricing, posting the same rate across broad geographic areas. Our branch-based Deposit-β addresses these limitations by capturing depositor sensitivity at the branch level—that is, the profitability a bank can extract from its local depositor base—regardless of whether it sets rates uniformly or differentially. If a bank varies rates across branches, high-β branches will exhibit lower spreads (and thus lower profits) than low-β branches. If, instead, the bank uses uniform pricing, high-β branches will experience larger deposit outflows when rates rise, either because local competitors post more attractive rates or because rate-sensitive customers shift funds into substitutes such as money market funds. In such cases, banks may attempt to retain deposits in high-β markets through ancillary services, advertising, or costly promotions.[1] In either case, Deposit-β provides a consis-

[1]This kind of behavior was used widely during the late 1970s to alleviate disintermediation from binding interest rate caps on deposits. Some banks went so far as offering expensive gifts such as televisions to retain deposits.

tent ranking: low-β branches generate more value for the bank than high-β ones.

Our location-based Deposit-β strongly predicts both branch closures and openings, but operates differently across the two margins. Incumbent banks are less likely to close branches in areas with price-insensitive customers (low β), as such customers are especially profitable and easy to retain. In contrast, potential entrants are less likely to open branches in these same areas, since low rate sensitivity makes depositors difficult to attract away from incumbents. This asymmetry helps explain why the industry has been—and will likely continue to be—reshaped.

As a complementary exercise, we replace Deposit-β with its demographic determinants in the regressions. Consistent with the interpretation above, closures are more common in areas with highly educated residents and those more exposed to the stock market—individuals more likely to adopt digital banking technologies and more interest-rate sensitive (Haendler, 2022; Jiang, Yu, and Zhang, 2022; Koont, 2023). We also find that depositors in these areas visit branches less frequently and travel greater distances when they do, reducing the strategic value of maintaining a physical presence. Finally, the marginal impact of deposit rate sensitivity on closures increases sharply after the COVID-19 pandemic, a 'teachable moment' when many people learned that technology could substitute for physical proximity and remote work arrangements reinforced online rather than in-person interactions.

The relationship between Deposit-β and branch restructuring—both closures and openings—is stronger for large banks than for small ones. This difference is especially evident in the years following the COVID-19 pandemic, which marked a sharp increase in branch closures, particularly among large banks. Large banks responded more when deciding which branches to close or where to open new ones, whereas small banks exhibit weaker and less consistent patterns. These differences likely reflect underlying variation in customer composition and strategic focus: large banks tend to attract more financially sophisticated customers—those with higher income, education, and digital adoption—who are more interest-rate sensitive. This sorting is consistent with evidence from Narayanan and Ratnadiwakara (2024), who use cell phone data to show that large-bank branches are disproportionately visited by customers from more affluent and educated areas. Kundu, Muir, and Zhang (2024), also studying the largest banks, find larger declines in branches among those paying high deposit rates. As a result, large banks are more active in adjusting their branch networks in response to changes in the profitability of their deposit base. d'Avernas, Eisfeldt, Huang, Stanton, and Wallace (2023) find that large bank customers value the broader set of financial services they provide and are willing to accept lower deposit rates to stay with the bank. We find, however, that the large banks increase their rates more aggressively relative to small banks when market rates rise, a finding that is consistent with Drechsler, Savov, and Schnabl (2021) who document a positive relationship between bank size and deposit betas.[2]

Compared to deposits, we find at best only weak evidence that lending variables can explain branch restructuring. This is surprising given that much of the prior banking literature has demonstrated the importance of physical distance between bankers and borrowers (e.g., Petersen and Rajan (2002); Berger, Miller, Petersen, Rajan, and Stein (2005)). But technology has significantly reduced the importance of distance. Until recently, most business sales were conducted largely using cash, which necessitated close physical proximity to a bank branch, if nothing else as a means to safeguard cash receipts. Today, businesses accept an increasing fraction of their sales from electronic payments (as opposed to cash), reducing the need for local branches for security-related purposes. Beyond that, the information environment has also changed significantly, again because payment flows are now dominated by electronic means.[3] As such, physical proximity no longer mat-

[2]Notably, the sample period in d'Avernas et al. (2023) ends before the COVID-19 pandemic, when these effects become most pronounced.

[3]Penetration of phone-based payments technologies has been faster in many parts of the world than in the US. As a result, for example, the number of branches per capita has fallen twice as fast in the EU as in the US. In the Netherlands, to take an extreme case, the number of bank branches has fallen by 85% (https://fred.stlouisfed.org/series/DDAI02NLA643NWDB).

ters much for information production.[4] For these reasons, we argue that the demand for lending does not help explain branch restructuring because bank location matters little for effective credit provision by banks (or other lenders, such as Fintechs).[5]

In the final part of our analysis, we use cell phone mobility data to track branch usage, focusing on the decline in visitors around the pandemic and the distances traveled by those who still visit. These measures help predict branch closures but are less informative for explaining openings. Including them in our regressions attenuates the effect of deposit rate sensitivity only slightly, which continues to exhibit strong explanatory power. The reason is that branch usage and rate sensitivity are strongly correlated, as both are shaped by local demographics. This finding reinforces our core argument: in areas with sophisticated residents, technology substitutes for brick-and-mortar banking, reducing the value of deposits to banks. Technology both raises depositors' interest-rate sensitivity and diminishes the amenity value of geographic proximity. People who rely on mobile apps and the internet do not value nearby branches, making demographics the common driver of branch usage, deposit sensitivity, and ultimately, branch closures.

We contribute to a nascent literature studying drivers of branch closures. Keil and Ongena (2024) study the de-branching regime as we do, but that paper emphasizes variation across banks in technology adoption. Similarly, both Haendler (2022) and Jiang et al. (2022) show that banks offering customers online or phone-based access are more likely to close branches. Koont (2023) argues that bank investment in digital technologies leads to branchless competition. Our approach takes banks' investments in technology as given (by absorbing bank-time effects) and instead focuses on how branch-level variation in the customer base explains closures. As such, our work is complementary to theirs. The core

[4] Buchak, Matvos, Piskorski, and Seru (2018) focus on the increasing market share of fintech lenders in the mortgage space and Gopal and Schnabl (2022), who report a high and growing share of lending to small businesses by non-banks. For a review of the growing role of Fintech lenders generally, see Berg, Fuster, and Puri (2022)

[5] Note that we are not claiming that bank relationships no longer matter; nor are we arguing that bank-borrower lending relationships are no longer sticky, as has been documented across many studies. We are instead arguing that the physical distance between banks (or bankers) and borrowers matters much less than in the past.

difference is that our effects depend on variation in customer adoption of technologies – that is, customer demand for non-branch access to their funds - which lowers the value of bank branches. We shut down variation in the supply of technology by controlling for bank-year and county-year fixed effects.

Evidence from other jurisdictions supports the view that tech-savvy customers lower the value of a physical branch location. Yuan, Li, and Zhang (2023) show that younger customers (Gen Z) who switch to similar banking products offered by Fintech firms leads to a rise in both the number and share of branch closures in China. Zimin and Semenova (2022) show that higher levels of financial digital literacy are related to de-branching in Russia. Consistent with our arguments, Benmelech, Yang, and Zator (2023) and Koont, Santos, and Zingales (2024) argue that digital banking reduces depositor stickiness, both with regard to changes in market interest rates and also around the SVB crisis.

Our paper complements Kumar and James (2025). While our paper focuses on understanding which, among a given bank's existing branch network, that bank chooses to close, theirs focus is on the role of the deposit franchise in explaining closure rates across banks. Like Sarto and Wang (2023), they emphasize that banks lose value in the low interest rate environment after the GFC because deposit spreads over market rates compress. Our empirical design complements theirs by absorbing these macro-level effects and instead focusing on how variation in the customer base influences branch-level closure decisions.

In contrast to our results, where we find little evidence that local lending affects branch closures, Cespedes, Jiang, Parra, and Zhang (2024), who study an earlier period (2011-2017), find that shadow bank entry affects bank closures by lowering local residual loan demand, especially at banks with a high cost of violating the Community Reinvestment Act (CRA). Their evidence, along with ours, suggests that the impact of lending may have changed in recent years, as information technology has become increasingly important.

To the best of our knowledge, this is the first paper to model branch closures and openings separately, rather than focusing only on the *net* change in branch counts within a locality. This distinction matters because incumbents and potential entrants face opposing incentives. Incumbents find areas with low depositor interest-rate sensitivity attractive, as they can extract rents from rate-insensitive customers by pricing deposits below market. Potential entrants, however, avoid these same areas because sticky customers are difficult to draw away from incumbents. Our results therefore highlight that Deposit-β is a more informative measure of local market power than the traditional HHI. Low β strengthens market power through two reinforcing channels: (i) incumbents exploit rate-insensitive depositors, as emphasized by Drechsler et al. (2017), and (ii) potential entrants face higher barriers because depositors in low-β markets are difficult to attract away from incumbents.

Our motivation stems from the widespread de-branching in the U.S. since the GFC, a process, we believe, that is far from complete. In fact, branch decline has proceeded nearly twice as fast in the EU, with some Scandinavian countries experiencing reductions of up to 90%. Information and communications technology has reduced the importance of physical branches, and our results show that banks recognize heterogeneity in customer technology adoption and adapt strategically by closing the least profitable branches first. Earlier literature emphasized that branch ownership and location introduced frictions in banking services.[6] These frictions are now being eroded by information technology, which renders geographic distance and proximity increasingly irrelevant. Taken together, our evidence suggests that branch networks will continue to shrink and play a diminishing role in shaping deposit pricing and credit availability.

[6] For example, areas with highly concentrated ownership of branches experienced less competition in both deposit and lending markets. Branch closures reduced local small business lending (Nguyen, 2019). Capital flows were also shaped by ownership networks across local areas (Gilje, Loutskina, and Strahan, 2016; Cortés and Strahan, 2017). The most powerful evidence of the importance of branching emerged from studies of deregulation of restrictions on branch ownership within and across state lines (Jayaratne and Strahan, 1996; Rice and Strahan, 2010). Following such deregulation, credit and deposit market competition improved, capital mobility increased, and the supply of financial services expanded.

1. A Framework to Understand Branch Restructuring

We follow Drechsler, Savov, and Schnabl (2023), who construct a simple measure of the profitability of bank deposits - the deposit franchise value (DF) - equal to the present value of gains associated with pricing the current stock of deposits at below-market rates of interest (so the deposit interest rate $r_i^d < r^f$, the market interest rate). In this framework, banks set their deposit rate equal to a fixed fraction of the market rate (so, $r_i^d = \beta_i \times r^f$); β_i represents the deposit "mark-up" over marginal cost (the market rate of interest) or, equivalently, the interest-rate sensitivity. We apply this framework to the branch level, as different branches held by the same bank have different clientele depending on their location, thereby facing different levels of interest-rate sensitivity. Drechsler et al. (2023) also assume deposits run off equally in each year over the next 10 years, so the profits generated at each branch depends on three factors, as follows:

$$DF_i = D_i \times (1 - \beta_i - \frac{c_i}{r^p}) \times [1 - \frac{1}{(1 + r^p)^{10}}]. \tag{1}$$

Where D_i = total deposits at branch i, $\beta_i = \Delta r_i^d / \Delta r^f$ is the price sensitivity at branch i (and represents the level of market power), r_i^d is the interest expense on deposits per dollar of deposits, r^f is the Fed Funds rate, r^p is the the long-term interest rate. In (1), c_i captures the annual non-interest (operating) cost of holding each dollar of deposits. In our models of branch closures (and openings), we include separate variables to capture each of these factors: the log of the amount of deposits at the branch (which is observable directly), the β_i in each branch (not directly observable), and the per-dollar operating cost (c_i). Below we describe how we build the branch-level β_i. For operating costs, which depend mainly on local rents and wage rates, we absorb them with county-time fixed effects.

The DF framework assumes that banks price deposits differentially across their branches based on the local rate sensitivity. But different levels of interest-sensitivity will capture the rank-ordering of each branch's value to its owner even under uniform pricing, meaning cases in which the bank sets a single deposit rate across all branches in a given region or even across its entire network. This follows because deposit quantities (D_i in (1)) would adjust, being higher in areas with low-β customers (because the uniform-pricing bank would set deposit rates on better terms than the local market would otherwise bear) and vice versa in areas with high-β customers.

We argue that innovations in both payment systems (e.g., PayPal, Venmo, Zelle, etc.), along with easy access to deposits via the internet and smartphones, have increased depositor sensitivity to market rates (thereby lowering bank pricing power) and also reduced the value to them of close proximity to a bank branch. We take these technological changes in the basic financial infrastructure as given, but exploit the fact that customer adoption of these technologies exhibits substantial heterogeneity. Younger and better-educated households, for example, interact with their banks via technology at higher rates and earlier than older and lower-income households (FDIC (2023)). Hence, differences in the local demographics faced by different branches will drive variation in the value of those branches. We can represent the relationships we have in mind schematically as follows:

- Local Demographics $\rightarrow$ Interest-Rate Sensitivity
- Local Demographics $\rightarrow$ Branch Usage
- Interest-Rate Sensitivity and Branch Usage $\rightarrow$ Branch Openings and Closures

These relationships capture the central mechanism in our analysis. First, local demographics—such as age, education, income, and stock market participation—affect how depositors interact with banks. In areas with more financially sophisticated households, depositors are more likely to adopt digital technologies, resulting in higher interest-rate sensitivity and a lower deposit franchise value (as in (1)). Second, this same demographic variation drives patterns of branch usage: people in sophisticated zip codes visit branches less often and travel farther when they do, consistent with their substitution toward online and mobile banking channels. Third, branches that serve such communities—those with both low DF and low usage—are prime candidates for closure, as they offer less pricing power and limited in-person engagement. Finally, areas with high interest-rate sensitivity (low DF) but relatively higher potential usage (e.g., less sophisticated markets not yet fully penetrated) may still be attractive for entry, as new branches in those areas can target customers who remain dependent on physical access but are not yet served by the bank.

This framework underlies our empirical design and helps explain the observed heterogeneity in restructuring decisions across banks, branches, and local markets. Our empirical section below estimates these relationships in three steps: 1) we first estimate the relationship between local demographics and rate sensitivity at the bank level, and then use that model to compute rate sensitivity at the branch level; 2) we then estimate how demographics affect branch usage based on cell phone data; 3) we estimate how rate sensitivity and branch usage affect branch restructuring decisions. As argued by Egan, Lewellen, and Sunderam (2022), most of the value created by banks stems from payments-related services, which allow banks to raise and retain deposits at interest rates well below market interest rates (Lu, Song, and Zeng (2024)). Drechsler et al. (2017) show how this pricing power over deposits leads to a novel channel of monetary policy transmission driven by the cyclicality in bank deposit pricing. As such, we focus most of our attention on changes in the value to banks of paying below-market interest rates on deposits. In our last set of tests, we introduce branch usage metrics to the models, which are only available during the most recent portion of our sample.

2. Data Sources

We combine data from several sources to construct our analytic samples. This section describes the underlying datasets and how we use them in the analysis.

2.1. Summary of Deposits

We use the FDIC's annual *Summary of Deposits* (SOD), which allows us to measure the amount of deposits and location of each bank's branch network in June of each year, and also to observe branch openings and closings. We estimate our restructuring models during the years from 2001 to 2023. A branch is 'closed' ('opened') in year t if it appears (does not appear) in June of year t in the SOD dataset but does not (does) appear in the June of year $t+1$. This definition can be established with certainty not only because the SOD contains a branch-based ID variable, but also because it contains detailed data on each branch's physical location (e.g., latitude and longitude, as well as state, city and street address). Figure 2 reports the fraction of branches closed (Panel A) and opened (Panel B) in each of the years we study, split by bank size (with large defined as banks with more than $100 billion in assets). Branch opening rates exceed that of closings in every year prior to the GFC, and vice versa in every year after.[7] Branch closures spike during the year of and following the COVID-19 Pandemic, with large banks closing nearly 8% of their branches in 2020 - where again we define 2020 as the period between June 2020 and June 2021.

2.2. Bank Call Reports

The Federal Financial Institutions Examination Council (FFIEC) requires US banks to file information on their financial health and performance at the end of each quarter and these

[7] We have verified that branches identified as openings are indeed new, as opposed to a branch which may have been closed and subsequently purchased by a bank entrant.

are made publicly available. These “Call Reports” provide a breakdown of balance sheets and income statements.

2.3. Demographic data

To capture local demographic factors, we use the American Community Survey (ACS) 5-Year Data, which provides economic and socioeconomic information across various geographical levels in the United States. Because ACS data begin in 2009, we use 2009 values—based on 2005–2009 averages—to proxy for earlier years in our analysis. We use the census tract level information on income, education, and age, and we also capture a measure of stock market participation using zip code level data from the IRS Statistics of Income (SOI) on Individual Income Tax Returns, specifically the fractions of tax returns reporting dividend income and capital gains.

2.4. Branch Usage data

We use the Advan (formerly SafeGraph) Monthly Patterns dataset, which provides aggregated raw counts of visits to points of interest (POIs) in the US, gathered from a panel of mobile devices. This anonymized and aggregated dataset provides details on monthly visitor frequency, duration, the origin census block group, and the distance the median branch visitor traveled. The dataset initiates from January 2019 and ends in 2023; however, we do not have usage data during the height of the pandemic. We use these data to identify how many customers use each bank branch and how far the median branch visitor traveled. Because of its limited coverage of branches closed prior to 2022, and because we lag the usage measures, we report branch closure models controlling for usage only for 2022 and 2023.

2.5. Other Data Sources

In addition to the primary datasets outlined above, we incorporate several other data sources to construct control variables for our regressions. The Home Mortgage Disclosure Act (HMDA) data is used to calculate mortgage loan growth at the county level, while the Community Reinvestment Act (CRA) data is used to calculate small business loan growth at the county level. County Business Patterns (CBP) data is used to calculate establishment growth and payroll growth at the county level. Additionally, the Federal Housing Finance Agency (FHFA) Underserved Areas data is used to create a zip code-level dummy variable indicating whether a zip code is classified as a low-to-moderate income (LMI) area, defined as having a median income below 80% of the area median income.

3. The Cross Section of Deposit Sensitivity

3.1. Bank-Level β and Its Determinants

As shown in (1), the value of the deposit franchise depends on the quantity of deposits at each branch; the deposit-β, which captures market power and depositor behavior; and operating costs. The first and third components are straightforward, as the SOD contains each branch's total deposits, and costs can by stripped out with local time-varying fixed effects. This section describes how we build the β_i.

We focus on the last three monetary tightening cycles, using bank-level realizations of β: first for the 2004–2006 (early) cycle, second for the 2016–2019 (mid) cycle, and third for the 2022–2023 (late) cycle, applying a consistent estimation framework in each period. We first estimate cross-sectional regressions to reveal how local factors affect the deposit β. This allows both the mean level of β to evolve over time and also allows the cross-sectional effects of demographics and concentration to vary over time. Realized β equals the change in bank annualized interest expenses per dollar of deposits over each cycle (from Bank *Call Reports*), normalized by the change in Federal Funds rate over that cycle (= 4.25% in the early cycle, 2.5% in the mid cycle, and 4% during last cycle). We use just the increasing portion of each rate cycle. The end of both the mid and the late cycles coincide with crises (GFC and the COVID Pandemic), making the subsequent rate declines and bank reaction to those declines difficult to interpret, and not reflective of their normal response to market-rate changes.[8] The sample period in the third cycle ends at the first quarter of 2023 to ensure that changes following the Silicon Valley Bank (SVB) collapse do not impact our estimations.

To build cross-bank local drivers of β, we average the demographic and market characteristics of residents living near each bank's branch (based on zip code), weighted by the amount of deposits each bank holds in each of its branches.[9] These regressions are structured, as follows:

$$\beta_{j,t} = \sum \gamma_t^k D_{j,t}^k + \eta_t HHI_{j,t} + \text{Other controls} + \varepsilon_{j,t} \tag{2}$$

where j represents bank, t represents one of the three rate cycles, k represents four demographic variables: age (using three quartile-binned indicators), log of mean family income, the fraction of tax filers reporting stock-based income, and the fraction with a college degree. We average each of these demographics across each zip code in which bank i owns its branches, weighted by deposits in each branch. In addition, we capture the deposit-weighted average level of concentration across each bank's markets ($HHI_{j,t}$), where markets are defined at the county level. The other control variables include bank-

[8] Banks received massive deposit inflows during this time due to large transfer payments to households, workers and firms under the CARES Act. These exogenous shocks to deposits may disturb the normal pricing reaction of banks to a decline in interest rates which would not be a good representation of their pricing power.

[9] We rely on the pooled models (i.e., large and small banks together) to identify the effects of local variables on the deposit franchise. Estimating these models for large banks alone would be problematic because they own branch networks distributed widely across the country, thus restricting the variation in their exposure to (averaged) local factors.

level population density, calculated as the county-level population density weighted by deposits in each county, a measure of bank size (log of total assets), transactions deposits as a percent of total assets, and uninsured deposits as a percent of total assets. The dependent variable in Equation (2) equals the change in the interest expenses on deposits per dollar of deposits in each cycle, scaled by the corresponding change in the Fed Funds rate.

Table 1 reports summary statistics for the regression samples in the three cycles, separated for large (>$100 billion) and small banks. Explanatory variables are measured at the beginning of each rate cycle. For small banks, the mean realized β_i ranges from 0.17 to 0.23; for large banks, the β_i ranges from 0.24 to 0.32. Large banks operate in areas with younger, more educated, wealthier populations that have higher rates of stock market participation than small banks. These demographic differences do not vary much over time across large and small banks. Small banks are more likely to have branches in rural areas.

Figure 3 reports histograms of the bank-level β_j values in Panel A, split by the three monetary tightening cycles and by bank size. Large banks have higher βs on average in all three cycles (recall Table 1), although there is substantial overlap in the distributions.

Table 2 reports estimates of Equation (2) for the three rate cycles. Age, income and education are all correlated with bank pricing power as expected (columns 1-3). Banks with (potential) customers near their branches who are younger and more highly educated have *lower* pricing power (higher β). The age effect is driven by the oldest quartile. Increasing the share of a bank's clientele with a college degree by one sigma (from the large-bank sample) raises β by 0.08 (=0.15 x 0.56) in the late cycle, for example. Banks have higher pricing power in areas with higher income. Concentration (HHI) enters all of the models negatively (suggesting greater bank pricing power in more concentrated areas). In contrast, local population density – which itself is strongly correlated with HHI - has a positive impact on β, with increasing importance over time. In other words, people living in urban areas are more price sensitive, and this difference in sensitivity has grown sharply over time. Large banks also exhibit much higher βs than small, particularly in the last cycle.[10]

Columns 4-6 of Table 2 report a more parsimonious model which collapses two demographic characteristics into one: the fraction of residents in 'sophisticated' zip codes. We build the zip-code classification by flagging localities with above-median education and above-median stock market participation. We use this indicator to differentiate areas dominated by financially sophisticated people versus those without. We include age and income in these models as separate factors. As the results show, the deposit β is consistently higher in sophisticated areas, and the impact of financial sophistication increases in the late cycle relative to the first two. For context, a bank raising all of its deposits in areas with financially sophisticated depositors would have a deposit-β that is 7%-10% higher, compared to a bank raising all of its deposits in areas with less-sophisticated depositors. Such a bank would pay 7-10 basis points more per 100 basis points increase of interest rates.

3.2. Predicted β at the Branch Level

We construct branch-level measures of β_i applying the coefficients from Equation (2) to each bank's branches using the demographic measures from that branch's zip code (opposed to the average across all branches, as in Equation (2)). We use the coefficients from the early interest-rate cycle for the years 2001-2014, from the mid cycle for 2015-2019, and the coefficients from the late cycle for the years 2020-2023.[11] Since banks own branches in zip codes with different demographic factors, this procedure generates within-bank variation in the interest-rate sensitivity which we exploit in our closure and openings models.

[10] Note that we absorb size effects in our closure models with fixed effects.

[11] Our aim is the allow the marginal effects of customer demographics to shift over time. We recognize that the coefficients we use are not strictly out-of-sample. Changing this mapping has little effect on our results because the coefficients are fairly stable, and because the demographic variables are very persistent.

Panel B of Figure 3 shows the distribution of predicted β_i at the branch level. The densities reveal substantial within-bank heterogeneity, reflecting variation in local demographic characteristics across branch locations. This variation provides the identifying power for our branch-level analysis of closure and decisions, as it allows us to compare branches within the same bank that differ in the profitability of their deposit base.

The persistence of both bank-level and branch-level differences over time is illustrated in Figure 4, which compares the predicted β across interest rate cycles. Panels A and B plot the bank-level values for the early vs. mid cycles and mid vs. late cycles, respectively. Panels C and D show the same comparisons using the branch-level predicted values. As expected, the cross-sections are highly correlated over time, with a tighter relationship at the branch level. This reflects the stability of both the explanatory variables (demographics change slowly) and the coefficient estimates, as documented in Table 2. Put simply, branches with above-average β early in the sample tend to remain above-average in later years. The figure also shows that their β values are generally higher in the post-pandemic period. Between the mid and late cycles, the fitted line rotates upward around the 45-degree line, consistent with a sharp increase in the effects of bank size and population density on bank-level βs. Larger banks and those in urban areas now face higher βs, and these effects are strengthening over time. We use these predicted values in our core branch closure models below.

4. Branch Usage, Technology Adoption, and the Role of Demographics

As discussed earlier, customer demographics shape branch restructuring through two main channels: by influencing banks' pricing power and by affecting the value customers place on physical proximity to a branch, particularly through differences in technology adoption. The COVID-19 pandemic provided a shock to this valuation, as many individuals became more comfortable using technology to substitute for in-person interactions. To capture these changes, we begin by examining shifts in branch foot traffic between 2019 and 2021 using Advan cell phone data, where *Drop in Visits* is defined as (Traffic in 2019 – Traffic in 2021) / Traffic in 2019. We interpret larger declines in foot traffic as indicative of greater reliance on digital banking relative to in-branch services. We also use the Advan data to measure the median distance traveled by visitors to reach a branch in 2019. These metrics, based on location and time-stamped mobile device data, serve as inputs into the following model:

$$\text{Usage}_{j,i} = \sum \gamma^k D_i^k + \text{Other controls} + \varepsilon_{j,i} \tag{3}$$

where j indexes banks, i indexes branches, k indexes the demographic variables observed in each branch's zip code.[12] The control variables include a bank fixed effect, state fixed effect, the county-level population density, and the log total deposits held in branch i.

Table 3 reports the estimates of equation (3) with all four demographic factors (Panel B), and also the more parsimonious version in which we collapse education and stock-market participation into a single sophisticated indicator (Panel A), as in Table 2. Regressions are split based on bank size.

These results show a strong effect of local demographics on branch usage. For both large and small banks, usage declines sharply around the pandemic: the mean decline in foot-traffic between 2021 and 2019 equals 31% for large-bank branches and 15% for small. The regressions show that this decline is higher in areas with more sophisticated clientele.[13] The number of visits, for example, drop 7 percentage points more at large-bank

[12] As noted, we do not have cell phone data during the Pandemic year of 2020. Even if we did, these data would be highly unrepresentative of normal behavior due to the effect of lockdowns and general fear of COVID contagion.

[13] Sakong and Zentefis (2025) find higher demand for branches among high-income populations, based on foot-traffic prior to the Pandemic. Our results suggest, however, that demand for branches fell most sharply during the pandemic among financially sophisticated populations.

branches located in these areas (and 10 percentage points more for small banks). Moreover, visitors from sophisticated areas are on average traveling from further away when they do visit a branch. In other words, customers in financially sophisticated locations value physical branches less than customers in other areas. Age also correlates strongly with usage, with foot-traffic falling most for areas with many young people (the omitted group in the regression). As the model shows, the age effects on the drop in visits is monotonic, while the effect on distance is non-monotonic across the distribution.

Next, we turn to studying how the two bank branch usage measures evolve dynamically around the Pandemic. To examine these changes, we estimate a regression of the following form:

$$\text{Usage Metric}_{i,m} = \sum_{m} \beta_m \times \text{Sophisticated zip} \times (month = m) + \text{Other controls} + \text{Fixed effects} + \varepsilon_{i,m} \tag{4}$$

where i is the branch and m is the month. The regression includes bank, month, and zip code fixed effects. The coefficient captures the differential effect of financial sophistication on branch usage across months, relative to the omitted base month (January 2019).

Figure 5 reports the estimates with the corresponding 90% confidence intervals, presented separately for large and small banks. Panel A uses monthly visits as the dependent variable and Panel B uses the natural logarithm of the median travel distance to the branch. The clear pattern in Figure 5 is that the number of visitors to branches drops more in financially sophisticated areas (i.e., the betas plot below zero), and the effect of financial sophistication grows around the pandemic. These effects are most pronounced for the small banks (consistent with the regressions in Table 3).

In contrast to visits, the average travel distance to branches showed no significant change, indicating that while fewer sophisticated people visited branches in these areas, the geographical reach of branch visitors remained stable. As such, we focus on the cross-branch variation in travel distance, rather than its change around the Pandemic, in our models of branch restructuring below.

These findings align with broader societal shifts induced by the pandemic. Lockdown rules forced many people to rearrange their work schedules, leading to lasting behavioral changes, including a significantly higher prevalence of working from home. As Barrero, Bloom, and Davis (2023) document, only about 5% of Americans worked from home before the pandemic, but this figure surged to 60% during the lockdowns and has since stabilized at around 30%. Consistent the results in Table 3, the increase in remote work was far greater for individuals with a college degree or higher, reflecting their greater ability to adapt to remote work arrangements. The large difference in usage patterns based on demographics follows because higher income and more educated people were more likely to be able to work at home, compared to other people.

As noted, these cross-sectional and time series patterns suggest that more financially sophisticated people value proximity to a nearby bank branch less than other people. When the Pandemic hit, they reduced branch visits more, and traveled further when visiting a branch. Such effects, we argue, occur because these customers are accessing banking services increasingly with technology – internet and mobile banking – and more so than less sophisticated customers. The results of Tables 2 and 3 together imply that a branch's natural depositor clientele – the people living near the branch - drives both the pricing power of those branches (Table 2) as well as the usage of those branches (Table 3). In our last set of models, we test whether these two usage factors help explain branch opening and closing decisions.

5. Branch Closings and Openings

Our analysis so far has shown that local demographics drive variation in branch usage and deposit sensitivity, with more financially sophisticated areas exhibiting higher Deposit-βs and reduced reliance on physical branches. We now turn to examining how these factors influence banks' decisions about which branches to close and where to open new ones.

We begin by documenting the raw relationship between β and branch closures across monetary tightening cycles, as shown in Figure 6. The figure presents a bin-scatter plot of the annual percentage change in branches during each cycle, with bins defined by the branch-level predicted β (Panel A) or the bank-level actual β (Panel B). The pattern is clear—particularly during the second and third cycles: branches with more interest-sensitive customers (higher β) are more likely to be closed. This effect appears in both the branch-based and bank-based panels, with closure rates ranging from about 3 to 5 percent per year for high-β branches, compared to less than 2 percent for those with low β.[14]

5.1. Empirical Design

To examine these patterns more formally, we estimate three types of models to analyze the drivers of branch restructuring. The first focuses on deposit sensitivity, measured by branch-level predicted β. Since the data structure differs between openings and closings, we describe each in turn:

[14] A similar graphical analysis is not appropriate for branch openings, as banks face a wide range of potential locations for new branches and not just the zipcode where they actually open a branch. In contrast, branch closures are limited to zip codes where the bank already operates.

5.1.1. Closures

We use the following linear probability model where the dependent variable (*Closure*) indicates if a particular branch j owned by bank i was closed in year t:

$$\text{Closure}_{i,j,t} = \gamma Beta_{i,j,t} + \theta log(Deposits)_{i,j,t} + \text{Other controls} + \text{Fixed effects} + \varepsilon_{i,j,t} \quad \text{(5a)}$$

In (5a), we capture the effect of the deposit franchise with the first two terms, the quantity of deposits at the branch (*log(Deposits)*) and their interest-rate sensitivity (β) for branch j owned by bank i at time t, as described above. Our baseline estimates pool the branch-year data across the full 2001-2023 period. We report models with *state* $\times$ *year* and *bank* $\times$ *year* fixed effects, and we report models with *county* $\times$ *year* fixed effects as well. These granular fixed effects absorb variation in branch-level operating costs. Moreover, by including *bank* $\times$ *year* fixed effects (as well as *county* $\times$ *year* effects in some specifications), we fully absorb both the general trends in banking and technology, as well as heterogeneity in the supply of technology across banks. For instance, Haendler (2022) shows that large banks adopted and updated mobile apps earlier and more frequently than smaller banks. This approach absorbs supply-side differences in the quality and quantity of online and mobile banking services, as these are common across all customers of a given bank, regardless of branch location. In addition, the *county* $\times$ *year* absorbs variation in local access to technology, such as differences in investment in the quality of the cell phone network. Thus, identification comes solely from variation in the impact of local demographics (i.e., demand-side factors) on branch closures.

At this stage, we exclude measures of branch usage, as these are only available for the final two years of our sample. We also estimate the model separately for large and small banks, reflecting differences in customer demographics (d'Avernas et al. (2023)) and the potential variation in marginal effects due to differences in the quantity and quality of services offered.

To capture the potential effects of local lending and loan demand, we include the following: the (logged) level of mortgage originations and small business originations at the bank-county-time level, as well as the county-level three-year past growth rate of both measures. In principle, we could also build an analogous metric to the Deposit-β based on loan-market pricing power. However, available measures of loan pricing, such as average interest income on C&I loans, would be driven mainly by large borrowers; such loans would not reflect local pricing power. Moreover, most of the variation in observed lending rates reflects differences in risk rather than mark-ups from market power. Hence, we focus on quantity-based measures of local lending conditions.

In addition to these, we include market control variables such as the three-year past growth rate of county deposits, the county-level growth in the number of establishments, and payroll growth; these help capture local economic growth effects. Two M&A-related indicators are added: the first equals one if the bank has owned at least one branch in the zip code for the past three years, and the second equals one if the current branch was acquired by the bank in the past three years and bank has owned at least one other branch in the same zip code prior to the acquisition; these help capture any restructuring effects associated with M&A activity. Finally, we include an indicator for branches in low- and moderate-income (LMI) areas, as defined by the Community Reinvestment Act, where banks face regulatory pressure to lend locally.

5.1.2. Openings

To understand branch openings, we construct a $bank \times zipcode \times year$ dataset which captures candidate zip codes where each bank might choose to open a new branch. For each bank-year, we include all zip codes in the CBSAs where the bank owned at least one branch in the prior year, and we add all zip codes in CBSAs in which the bank opens a new branch in the current year. Note that the set of candidates zip-codes differs across banks and time. We also drop all zip codes in which no bank ever owns a branch during our sample. The dependent variable is set to one if the bank opens a new branch in the candidate zip code and zero otherwise.[15]

With this sample, we estimate linear probability models parallel to 5(a), although we replace the lagged log level of deposits in an incumbent branch with the log of (1+deposits) based on all bank branches located in the given zip code during the prior year (i.e., branches owned by competing banks). We build the lending variables analogously using lagged log values for county mortgage and small business lending volumes. Since potential entrants have no deposits (lending) from the prior period, we interpret this variable as a measure of the potential (or maximum) level of deposits a new bank could raise. As in 5(a), we estimate the base model with *bank* $\times$ *year* fixed effects, as well as *state* $\times$ *year* or *county* $\times$ *year*.

5.1.3. Reduced Forms

In our second set of models, we extend the analysis by using a reduced-form version of (5a) and its analog for openings, replacing the predicted Deposit-β with the underlying demographic and market concentration variables that were used to construct it. The regression specification is as follows:

$$\text{Closure}_{i,j,t} = \sum_k \gamma_t^k D^k_{i,j,t} + \eta HHI_{i,j,t} + \theta LnDeposits_{i,j,t} + \text{Other controls} + \text{Fixed effects} + \varepsilon_{i,j,t} \tag{5b}$$

Here, $D^k_{i,j,t}$ represents the k-th demographic variable at branch j owned by bank i and time t, and $HHI_{i,j,t}$ captures the concentration in branch i's market. These effects collectively capture the impact of the Deposit-β. Fixed effects again include *bank* $\times$ *year* and

[15]The latter zip codes - those in CBSAs where a bank opens a branch for the first time - are potentially endogenous because they are conditional on the bank entering the area. In Internet Appendix, however, we verify that our core results are similar if we exclude these observations.

state $\times$ *year* or *county* $\times$ *year*. We report similar regressions for the choice to open new branches.

This approach allows us to test which local variables are most tightly linked to branch restructuring decisions. In these models, we report an additional specification combining education and stock-market participation into a single financial sophistication measure.

5.1.4. Models with Usage

Our third set of models incorporates the two cell phone-based branch usage measures as right-hand side variables. These specifications allow us to assess the relative importance of pricing power (deposit franchise value) versus customer convenience or the amenity value of proximity.

For the closure analysis, we can directly observe the two usage measures, as we do in Table 3. Branch-level usage patterns, however, are potentially endogenous and may respond to depositor expectations that a given branch will close.[16] For example, if depositors are informed that their branch will close, they may increase their in-person visitations to the branch. Hence, we adopt a 'leave out' strategy to build the two usage measures, as follows: for each branch, we compute the average *Drop in Visits* and the average *Log(Distance Km)* for all other branches located in the same zip code. As such, we drop all branches which are located in zip codes without competing branches.

For openings, there is no latent endogeneity problem because banks can only form expectations of usage based on patterns observed for existing branches of other banks. So, we build the usage measures based on the zip-code level averages of *Drop in Visits* and *Log(Distance Km)* for all branches located in each bank's candidate zip codes.

As noted, although the Advan data start in 2019, we estimate these models only in 2022 and 2023. The industry (NAICS) codes for the closed branches were changed in 2021.

[16] In fact, by regulation banks are required to inform depositors of an impending closure by mail with at least 90 days notice. See https://www.fdic.gov/consumer-resource-center/2024-07/your-bank-branch-relocating-or-closing.

As a result, branches closed in 2020 and 2021 have different NAICS in the Advan data, which doesn't provide a historical time series of these codes by location. When creating the dataset, we initially filtered locations with NAICS code 522 to indicate a banking office, so by necessity we filtered out these locations due to the change in the NAICS to a different code.[17]

Across all three sets of models, we build standard errors by clustering at the bank level.

5.2. Results

We first present summary statistics of the branch-year panel sample used for the closure regressions, focusing on the years 2012 and 2019. Tables 4 and 5 provide summary statistics of key characteristics for the branch closure sample and branch opening sample, respectively. For both the dependent variables as well as the β and the level of deposits, we report the sample standard deviation (SD) as well as the "SD (within)," which removes variation explained by the bank-time and county-time fixed effects; we use that latter metric to assess economic significance of the regression results below.

The tables split the summary statistics by bank size to highlight differences between small and large banks. While many mean characteristics are similar across the two groups, there are notable distinctions. Large banks, for example, hold significantly more deposits per branch, with the typical branch holding more than twice as many deposits as those of small banks. Geographically, small banks are more prevalent in rural areas, as indicated by their branches being in regions with much lower population density.

5.2.1. Baseline Results

Table 6 reports our estimates of Equation (5a). We report the pooled sample (columns 1 & 2), and then the split-sample results by bank size (over versus under $100 billion in

[17] It is computationally prohibitive to standardize all the US addresses and then match only by the address without first filtering by the NAICS code.

assets) in columns 3-6. For each set of specifications, we report models with $state \times year$ fixed effects and separately with $county \times year$ fixed effects. For all banks, in columns (1) and (2), lower β leads to lower probability of a branch being closed. The magnitude is substantial across all banks, but also larger for the large banks. A one-standard-deviation increase in β (in 2019 $\approx$ 0.02 for large banks and 0.015 for small banks after removing variation explained by fixed effects), for example, leads to a increase in large-banks' branch closure probability of about 0.5 percentage points (column 4). This effect is economically important, equal to more than 10% of the unconditional mean closure rate (=4% per year for the large banks) during our sample. Beyond β, which captures local market power, higher levels of deposits in the branch from the preceding year also has strong power to predict branch closures for both large and small banks. Hence the franchise value or rents from deposits seems to drive closure decisions.

Unlike the deposit franchise value, lending has little power to explain branch closures. In the pooled model (column (1)), neither bank-level nor county-level growth of small business lending has statistical significance. Mortgage growth does correlate negatively with closures, but this is driven by small banks. We also see a marginally significant effect of small business lending growth on small-banks' branch closures (column 6). Comparing the collective power to explain closures illuminates the difference: in the pooled model the two deposit variables (Ln Deposits and β) have an F-statistic of 480.4; by contrast, the four lending variables have an F-statistic of just 2.96. The contrasting power of deposits v. lending suggests that the core purpose of bank branches (especially for large banks) is to support the deposit franchise, where banks remain dominant. On the other hand, banks have become increasingly *less* important as suppliers of local credit - mortgages and small business loans. Moreover, deposits constitute about 85% of all bank financing, while local lending comprises a small percentage of total bank investments (again, especially for larger banks).

The models also suggest that banks are much more likely to close branches acquired recently if they already had branch presence in the zip code, and less likely to close 'legacy' branches, meaning those which have not been acquired over the past three years. We find no evidence that banks close branches in localities defined as LMIs under the Community Banking Act; if anything, large banks are *less* apt to close branches in these areas.[18]

Table 7 reports the baseline estimates for branch openings. The DF again plays a central role in predicting entry, but with opposing effects depending on whether we focus on quantity or on price-sensitivity. Higher interest-rate sensitivity (which lowers DF) among local depositors is associated with *reduced* entry. A one-standard-deviation increase in β (in 2019 equal to approximately 0.02 for both large and small banks, after removing variation explained by fixed effects) raises the probability of opening a branch by 0.12% (=0.02 x 0.06, from column (4)), or about one-quarter of the unconditional opening rate of 0.42% for large banks.[19] Local deposit levels, in contrast, positively predicts entry, as does establishment growth. Hence, banks enter new markets which are 'rich' in deposits, but only when price sensitivity is high.[20]

Table 7 again suggests that lending has much less power to explain branch openings than deposits. The four local lending variables have some statistical power, but with inconsistent sign patterns. For example, both county-level mortgage growth and bank-county levels of small business lending are negatively associated with entry for the large-bank sample (column 3). For small banks, two of the lending variables enter positively (as one would expect), but the other two negatively. The results do show a strong and consistent positive effect of overall local economic conditions (i.e., establishment growth), but this effect does not pin down a deposit v. lending channel, as both would tend to be

[18] Banks are required to give regulators and local customers notice before closing a branch under Section 42 of the Federal Deposit Insurance Act. Hence, large banks may be concerned that closing branches in LMI areas could lower their CRA rating, which in turn could impinge on future acquisitions.

[19] For large banks, the unconditional branch opening rate declined from approximately 0.8% prior to the GFC to about 0.2% afterward. The corresponding rates for small banks fell from 0.3% to 0.09%.

[20] Consistent with our results on entry Begenau and Stafford (2023) show that deposits grow much faster at new branches compared to older ones.

positively related to a locally booming economy.[21]

5.2.2. Reduced Form results

Tables 8 and 9 reports parallel models of branch closures and openings estimated as reduced forms (as in Equation (5b)). Panel A reports the full sample, and Panel B split by size. We find that branch openings and closings, for both large and small banks, are more likely in areas dominated by financially sophisticated people. Each of these effects is consistent with our interpretation that the value of the deposits plays a key role in bank branching decisions via its link to market power from higher or lower levels of interest-rate sensitivity. Comparing these results with those from Table 2, we see that high levels of financial sophistication lead to higher Deposit-βs, to higher rates branch openings, and to higher rates of branch closings. Similarly, areas with younger populations have higher βs and more entry (Table 9). For closures, however, the effects of age are less consistent across banks of different sizes.

5.2.3. Estimations over time

Tables 10 and 11 report estimates of Equation (5a) during four regimes: the period prior to the GFC (2001-2007); the years affected by the GFC (2008-2011); the post-GFC / pre-Pandemic years (2012-2019); and the post-Pandemic years (2020-2023). Panel A reports the model for large banks, and Panel B small ones (with *county* $\times$ *year* or *state* $\times$ *year* effects). These results suggest that branches with high Deposit-βs are consistently most likely to be closed. The effects are largest after the Pandemic. For large banks, a standard-deviation decline in the Deposit-β (=0.0177) comes with an increase in closure probability of 0.7% (column (8)), equal to about 14% of the unconditional closure rate. As in the

[21] We have also estimated closure models which control for an indicator equal to one for zip codes with new branches opened within the past three years. These markets exhibit higher closure rates, but adding this variable has little impact on our core results. Similarly, zip codes with recent closures have a higher probability of entry (openings), but again adding this has little effect on our core results. See the Internet Appendix for these results.

baseline model, openings are also consistently higher in areas with high βs, both across time and also for large and small banks.[22]

To summarize, the effects of both the level and pricing of deposits across all models, across all types of banks, and across time tell the same story. First, incumbent banks *close* branches where the per-dollar economic rents are low and where the total amount of deposits in their branch are also low. Second, banks *open* new branches in areas with high levels of deposits held by incumbents (because they are entering to raise deposits), but only where local depositors are price sensitive (because they can't effectively draw deposits away from incumbents when customers are rate insensitive).

5.2.4. Adding Usage

Tables 12 and 13 report our estimates for closures (Table 11) and openings (Table 12) after incorporating usage. These models allow us to compare the relative importance of branch usage (from declines in foot traffic from 2019 to 2021) vs. banks' deposit pricing power (DF). The regressions include only the last two years of our sample (2022 and 2023) due to data constraints in the Advan cell phone data, as noted above. Both the results for openings and closings continue to show that the DF remains the dominant driver of branch restructuring. Adding the usage metrics attenuates the effect of β, from 0.24 to 0.12 for large banks (Table 12, Panel B, columns (2) vs. (4)); in contrast, the effect of the level of deposits does not change with usage added to the model. Consistent with expectations, areas which experience large drops in branch usage (*Drop in visits*) around the pandemic experience more closures. This effect represents the 'teachable moment' of the Pandemic, in which many people learned how to substitute on-line technology for in-person interactions. As such, it represents a large shock to the value of close proximity to a bank branch. In addition, we find consistent evidence that banks are more likely to close branches located in areas where customers travel from greater distances.

[22] In an earlier version of this paper we report consistent effects over time using year-by-year regressions rather than pooled ones across the four regimes.

The effects of usage on openings are less clear, however. Like closures, β continues to correlate positively with branch openings. However, we find some evidence - mainly from small banks - that openings also are higher in areas with large declines in foot traffic. This may reflect the fact the these areas are ones where technology adoption was greatest, which raises price sensitivity and also lowers the amenity value of close geographic proximity. We find essentially no explanatory power of travel distance in any of the openings specifications.

6. Conclusion

Banks opened new branches at a higher rate than they closed them until the GFC, when this pattern reversed sharply. We show that variation in economic profits generated from bank deposits helps explain branch restructuring patterns, as banks are most likely to close branches in areas with low franchise value due to high interest sensitivity of local residents. Technologies which make physical proximity less important and which lower the cost of moving funds to substitute investments, we argue, drove the regime shift in branching starting around 2010. In contrast to other research, our empirical design exploits different rates of technology adoption by bank customers, which varies depending on characteristics associated with financial sophistication. The results suggest that the 2020 Pandemic had a large effect on technology adoption, leading to a sharp decline in foot-traffic at branches and an overall rate of branch closure roughly double what had come before.

Our results point to the importance of analyzing industry structural change using gross measures of openings and closings. Incumbent bank incentives differ sharply from those of potential de novo entrants. As we show, entry is higher consistently across bank types and over time in areas where local residents have high price sensitivity – exactly the areas where incumbents are most likely to exit. Conversely, price insensitivity of depositors creates an endogenous entry barrier for greenfield investment, and helps explain why most bank extensions into new markets happen via M&A facilitated by deregulation, which allows an entering bank to buy the existing customer base.

Understanding the drivers of branch closures matters because branch-based frictions have traditionally mediated flows of capital across markets and have affected local-market competition in both deposit and credit markets. Such frictions reduce financial market efficiency and integration. Lowering these frictions through technology furthers a process which began in the 1980s with deregulation of restrictions on branching and interstate banking. As such, continued bank restructuring will likely improve the functioning of local financial markets further.

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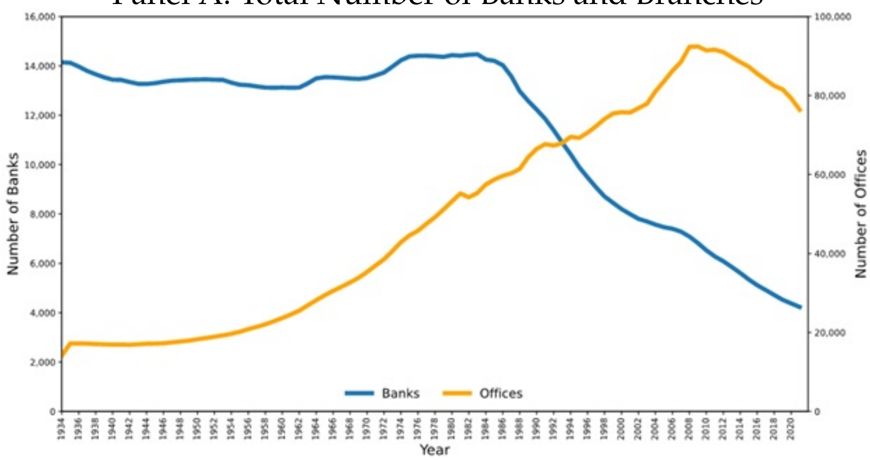
Figure 1: Change in Banks and Branches

This figure presents the evolution of the U.S. banking system. Panel A shows the total number of banks (blue line, left axis) and the total number of bank offices (orange line, right axis). Panel B displays the annual number of branch openings (blue line) and closures (orange line) from 2001 to 2023.

Panel A: Total Number of Banks and Branches



Panel B: Branch Openings and Closures

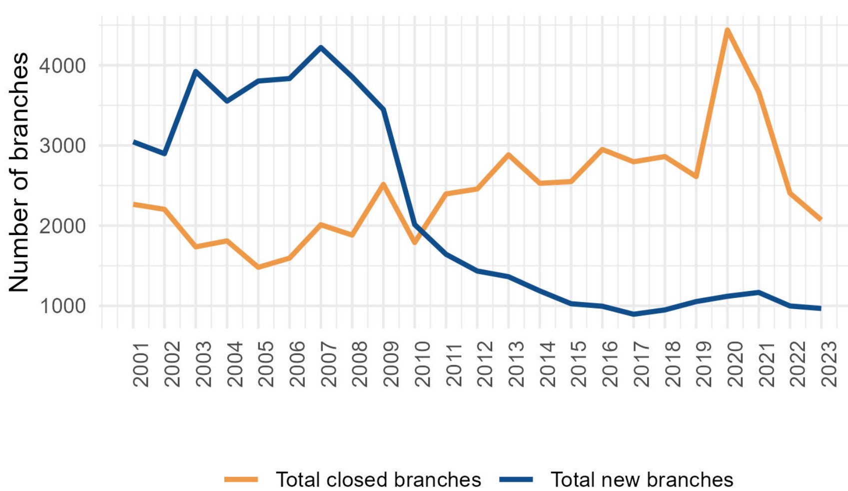
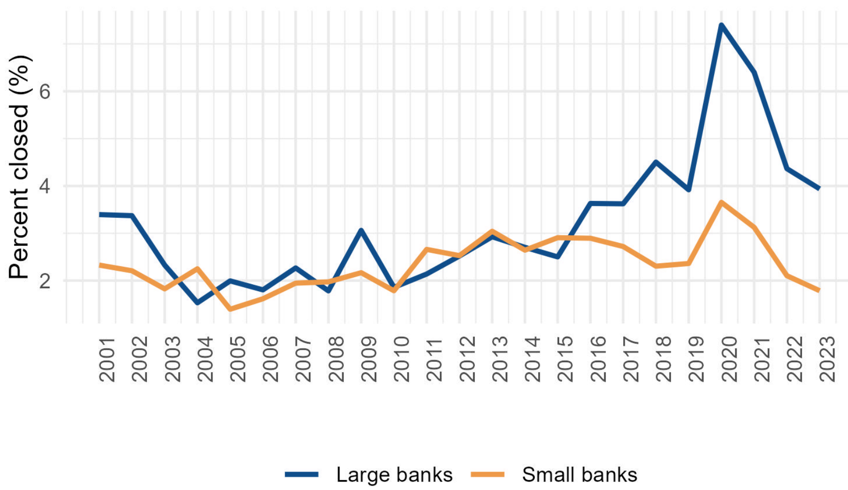


Figure 2: Percent of Openings and Closures

This figure presents the annual percentage of branches closed and opened by large banks ($\geq$ \$100 billion in assets, blue line) and small banks (<\$100 billion in assets, orange line) from 2001 to 2023. Panel A shows the percentage of branches closed each year. Panel B shows the percentage of new branches opened each year.

Panel A: Percent of Branch Closures



Panel B: Percent of Branch Openings

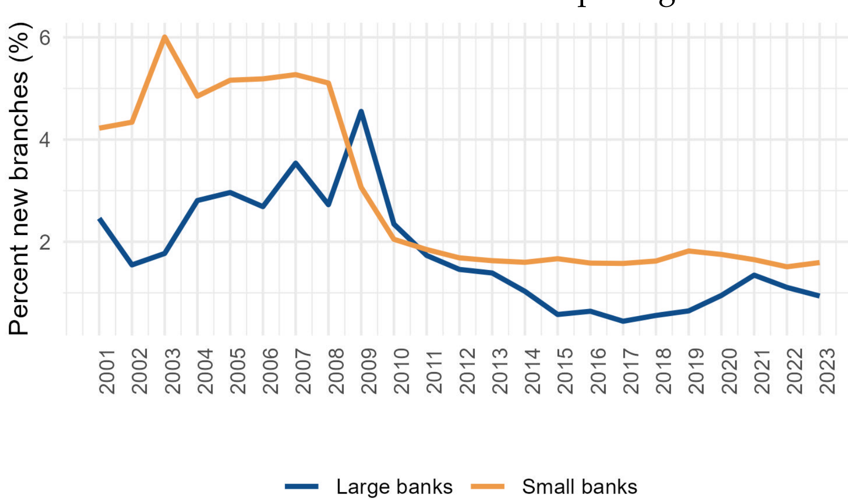


Table 1: Descriptive Statistics - Bank Level

This table presents summary statistics for the bank-level samples during three interest rate cycles, separately for large banks ($\geq$ \$100 billion in assets) and small banks ($<$ \$100 billion in assets). Panels A, B, and C correspond to the Late (2022-2023), Mid (2016-2019), and Early (2004-2006) cycles, respectively. For each group, the table reports the mean, standard deviation (SD), and selected percentiles for variables.

Panel A: Late Cycle (2022-2023)

	Large Banks (Obs = 27)				Small Banks (Obs = 4,296)			
Variable	Mean	SD	P10	P90	Mean	SD	P10	P90
Age	37.73	3.25	34.21	41.66	40.72	4.31	35.56	45.71
College educated fraction	0.57	0.15	0.41	0.80	0.29	0.14	0.16	0.49
Deposit-weighted Pop. density	0.52	0.14	0.36	0.69	0.15	0.21	0.01	0.57
Deposit beta	0.32	0.14	0.18	0.55	0.18	0.12	0.04	0.35
Family income (000)	88.81	39.06	59.00	117.00	58.28	18.45	39.00	80.00
Frac. deposits in sophisticated zipcodes	0.82	0.17	0.56	1.00	0.46	0.41	0.00	1.00
HHI	0.23	0.12	0.13	0.29	0.24	0.13	0.11	0.40
Stock market participation frac	0.32	0.12	0.19	0.45	0.20	0.08	0.10	0.29

Panel B: Mid Cycle (2016-2019)

	Large Banks (Obs = 38)				Small Banks (Obs = 4,872)			
Variable	Mean	SD	P10	P90	Mean	SD	P10	P90
Age	37.37	3.30	33.22	40.73	40.73	4.34	35.57	45.73
College educated fraction	0.55	0.16	0.38	0.77	0.30	0.15	0.16	0.51
Deposit-weighted Pop. density	0.51	0.15	0.28	0.69	0.15	0.21	0.01	0.58
Deposit beta	0.24	0.10	0.13	0.38	0.17	0.12	0.03	0.34
Family income (000)	89.10	36.37	58.70	117.20	58.97	19.02	40.00	83.00
Frac. deposits in sophisticated zipcodes	0.77	0.27	0.46	1.00	0.46	0.41	0.00	1.00
HHI	0.24	0.17	0.14	0.30	0.23	0.13	0.11	0.38
Stock market participation frac	0.30	0.12	0.16	0.45	0.20	0.09	0.10	0.30

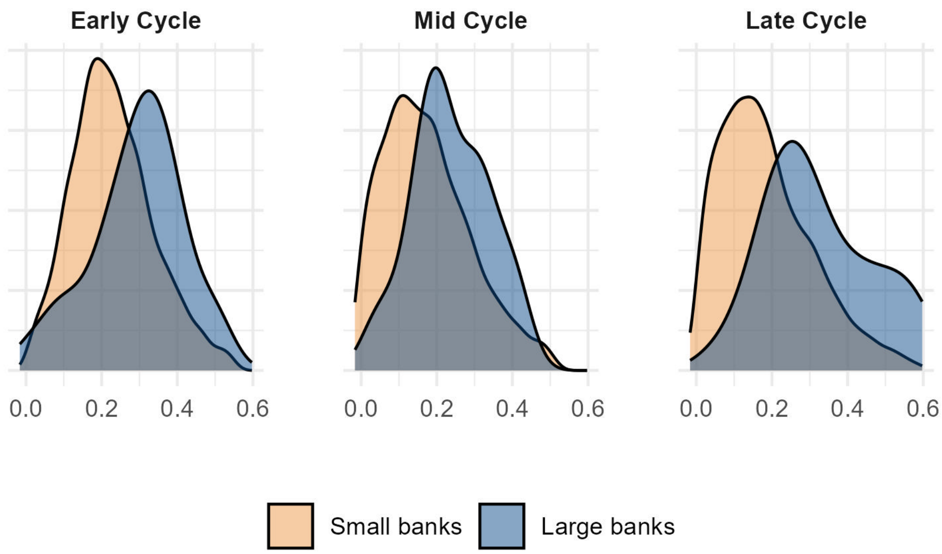
Panel C: Early Cycle (2004-2006)

	Large Banks (Obs = 32)				Small Banks (Obs = 5,515)			
Variable	Mean	SD	P10	P90	Mean	SD	P10	P90
Age	37.65	2.36	34.30	39.54	39.89	4.31	34.76	45.29
College educated fraction	0.51	0.13	0.38	0.72	0.27	0.13	0.14	0.45
Deposit-weighted Pop. density	0.48	0.12	0.30	0.65	0.13	0.19	0.01	0.51
Deposit beta	0.29	0.12	0.12	0.41	0.23	0.11	0.10	0.38
Family income (000)	71.03	23.75	48.00	90.70	50.36	15.34	35.00	70.00
Frac. deposits in sophisticated zipcodes	0.76	0.20	0.54	1.00	0.44	0.42	0.00	1.00
HHI	0.22	0.13	0.12	0.32	0.24	0.14	0.11	0.40
Stock market participation frac	0.29	0.10	0.22	0.39	0.20	0.08	0.11	0.29

Figure 3: Deposit Beta Distribution

This figure presents density plots of deposit beta values across three interest rate cycles: Early (2004-2006), Mid (2016-2019), and Late (2022-2023). Panel A displays bank-level beta distributions, while Panel B displays predicted branch-level beta distributions. In both panels, small banks (assets $<$ \$100 billion) are shown in orange, and large banks (assets $\geq$ \$100 billion) are shown in blue. Each subplot represents the distribution of beta values during the indicated interest rate cycle.

Panel A: Bank-Level



Panel B: Branch-Level

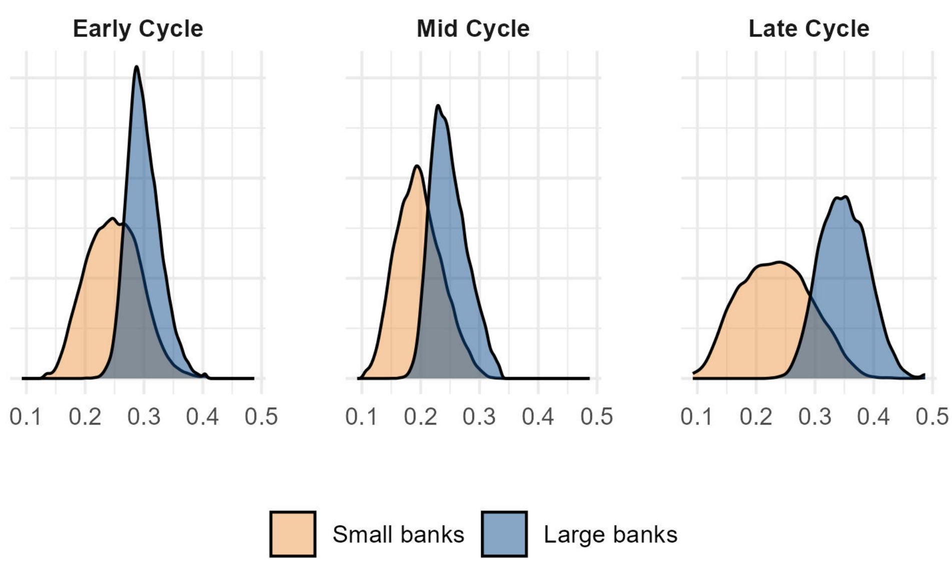


Table 2: Bank-Level Deposit Beta

This table presents regression estimates of deposit beta from Equation (2) across three interest rate cycles: Early (2004-2006), Mid (2016-2019), and Late (2022-2023). Columns 1–3 report specifications that include individual demographic variables with other controls. Columns 4–6 report a parsimonious specification that replaces the individual demographic variables with the fraction of deposits in sophisticated zip codes, defined as zip codes with above-median levels of both education and stock market participation. The dependent variable is the deposit beta. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Deposit Beta					
	Early Cyc.	Mid Cyc.	Late Cyc.	Early Cyc.	Mid Cyc.	Late Cyc.
	(1)	(2)	(3)	(4)	(5)	(6)
College frac	0.4026***	0.3353***	0.5624***			
	(0.0725)	(0.0600)	(0.1044)			
Stock market frac	0.0863	0.1987**	0.1409			
	(0.1004)	(0.0812)	(0.1435)			
Frac of deposits in sophisticated zipcodes				0.0763***	0.0659***	0.1039***
				(0.0138)	(0.0123)	(0.0208)
Age Q1-Q2	0.0068	-0.0002	0.0015	0.0028	-0.0016	-0.0031
	(0.0129)	(0.0107)	(0.0181)	(0.0127)	(0.0105)	(0.0177)
Age Q2-Q3	-0.0204	-0.0038	0.0097	-0.0234*	-0.0021	0.0064
	(0.0149)	(0.0123)	(0.0210)	(0.0141)	(0.0118)	(0.0199)
Age >Q3	-0.0070	-0.0641***	-0.0817***	-0.0094	-0.0556***	-0.0796***
	(0.0184)	(0.0171)	(0.0292)	(0.0173)	(0.0163)	(0.0278)
log(Income)	-0.1278***	-0.0926***	-0.1295***	-0.0832***	-0.0186	-0.0436
	(0.0267)	(0.0234)	(0.0395)	(0.0233)	(0.0201)	(0.0338)
County deposit HHI	-0.1294***	-0.0578*	-0.1440***	-0.1309***	-0.0493	-0.1428**
	(0.0371)	(0.0326)	(0.0554)	(0.0370)	(0.0328)	(0.0556)
log(Assets)	0.0059	0.0158***	0.0614***	0.0077*	0.0179***	0.0645***
	(0.0043)	(0.0033)	(0.0053)	(0.0043)	(0.0033)	(0.0053)
Population density	0.0394	0.0921***	0.2802***	0.1364***	0.1806***	0.4203***
	(0.0355)	(0.0285)	(0.0484)	(0.0313)	(0.0248)	(0.0422)
Transaction Accounts/Assets	-0.5629***	-0.3281***	-0.2854***	-0.5650***	-0.3274***	-0.2935***
	(0.0720)	(0.0484)	(0.0677)	(0.0721)	(0.0486)	(0.0678)
Uninsured Deposits/Deposits	0.7734***	-0.0529*	0.3780***	0.8114***	-0.0253	0.4153***
	(0.0364)	(0.0299)	(0.0512)	(0.0356)	(0.0298)	(0.0511)
Constant	1.773***	1.175***	1.059**	1.336***	0.4230*	0.1917
	(0.2844)	(0.2505)	(0.4218)	(0.2546)	(0.2190)	(0.3681)
Observations	5,539	4,906	4,405	5,539	4,906	4,405
R^2	0.17833	0.09642	0.20750	0.17544	0.08855	0.20282

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Figure 4: Deposit Beta Correlations Across Cycles

This figure presents scatter plots comparing deposit beta between pairs of interest rate cycles. The interest rate cycles are: Early (2004-2006), Mid (2016-2019), and Late (2022-2023). Panels A and B display branch-level observations; Panels C and D display bank-level observations. Each point represents a small bank (assets $<$ \$100 billion, orange) or a large bank (assets $\geq$ \$100 billion, blue). The x-axis reports beta in the earlier cycle, and the y-axis reports beta in the later cycle. The dashed line denotes the 45-degree reference line. The solid line represents the fitted relationship from a linear regression.

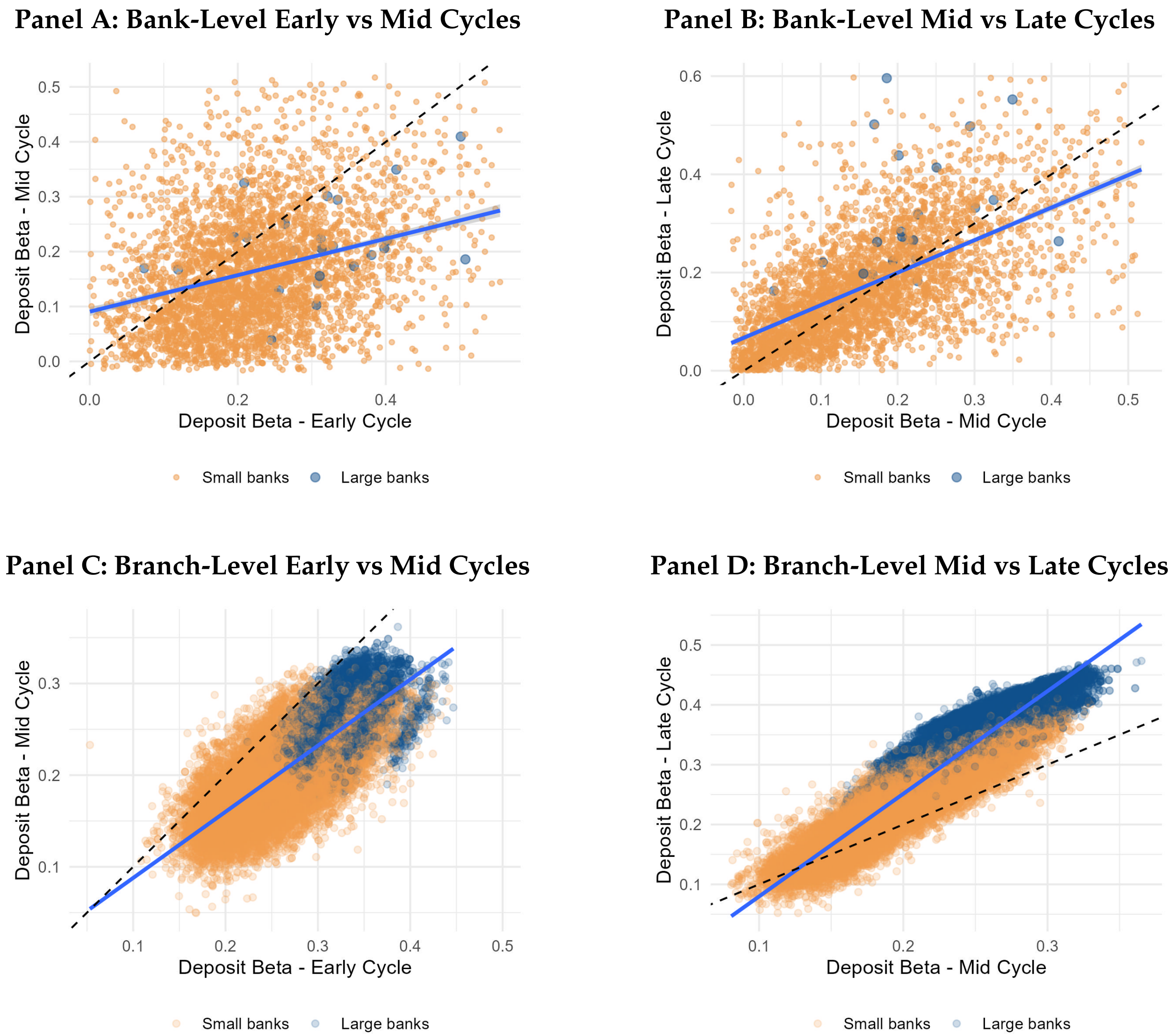


Table 3: Usage

This table reports regression estimates from Equation (3), examining branch usage and customer travel distance to branches. Results are shown separately for large banks (≥$100 billion in assets) and small banks (<$100 billion in assets). Panel A presents estimates from a parsimonious model using a single indicator for sophisticated zip codes. Panel B reports estimates using separate demographic variables, including age quartiles, income, education, and stock market participation. Columns 1–2 report regressions where the dependent variable is branch usage, defined as the percentage drop in visits from 2019 to 2021 for each branch. Columns 3–4 use the mean distance (in kilometers) that customers traveled to visit the branch in 2019 as the dependent variable. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A

	Drop in visits		log(distance km)	
	Large banks	Small banks	Large banks	Small banks
	(1)	(2)	(3)	(4)
Sophisticated zipcode	0.0652***	0.1034***	0.1841***	0.1212***
	(0.0099)	(0.0077)	(0.0187)	(0.0092)
Age Q1-Q2	-0.0200***	-0.0410***	-0.0661***	-0.0440***
	(0.0043)	(0.0080)	(0.0122)	(0.0099)
Age Q2-Q3	-0.0703***	-0.1039***	-0.0795***	-0.0515***
	(0.0076)	(0.0094)	(0.0204)	(0.0127)
Age >Q3	-0.0710***	-0.1264***	0.0280	0.0888***
	(0.0113)	(0.0124)	(0.0247)	(0.0168)
log(Income)	0.0053	0.0093**	-0.0698***	-0.0354***
	(0.0042)	(0.0043)	(0.0084)	(0.0051)
log(Deposits)	0.0185***	0.0278***	0.0291**	-0.0129**
	(0.0064)	(0.0040)	(0.0115)	(0.0057)
Population density	0.3688***	0.5439***	-0.3718***	-0.1433**
	(0.0405)	(0.0248)	(0.0282)	(0.0556)
Bank FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Observations	26,521	26,276	26,560	26,355
R^2	0.26680	0.43095	0.19958	0.33392
Note:			*p<0.1; **p<0.05; ***p<0.01	

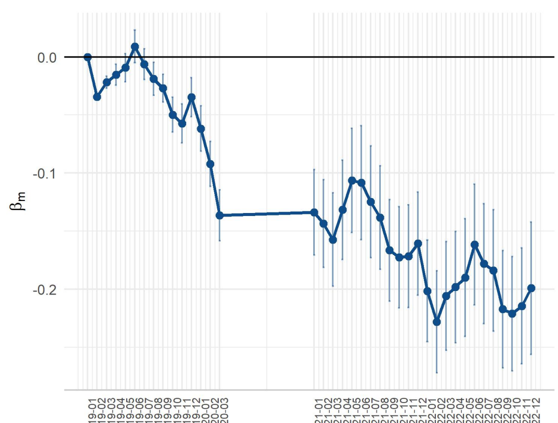
Panel B

	Drop in visits		log(distance km)	
	Large banks	Small banks	Large banks	Small banks
	(1)	(2)	(3)	(4)
College frac	0.4153***	0.4414***	0.4255***	0.1894***
	(0.0312)	(0.0318)	(0.0352)	(0.0465)
Stock market frac	0.0001	0.1851***	0.8185***	0.8561***
	(0.0281)	(0.0368)	(0.0703)	(0.0656)
Age Q1-Q2	-0.0381***	-0.0528***	-0.0455***	-0.0166
	(0.0042)	(0.0082)	(0.0095)	(0.0103)
Age Q2-Q3	-0.1025***	-0.1275***	-0.1011***	-0.0474***
	(0.0094)	(0.0098)	(0.0194)	(0.0126)
Age >Q3	-0.1156***	-0.1541***	-0.0560	0.0693***
	(0.0121)	(0.0124)	(0.0334)	(0.0169)
log(Income)	-0.0286***	-0.0139***	-0.1154***	-0.0509***
	(0.0046)	(0.0049)	(0.0076)	(0.0056)
log(Deposits)	0.0127*	0.0252***	0.0071	-0.0186***
	(0.0067)	(0.0038)	(0.0123)	(0.0055)
Population density	0.3058***	0.4568***	-0.4754***	-0.2577***
	(0.0353)	(0.0229)	(0.0293)	(0.0539)
Bank FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Observations	26,521	26,276	26,560	26,355
R^2	0.28	0.44	0.26	0.36
Note:			*p<0.1; **p<0.05; ***p<0.01	

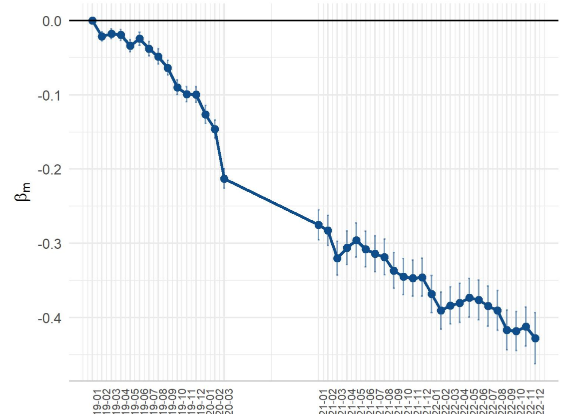
Figure 5: Dynamic Branch Usage

This figure illustrates the evolution of branch usage metrics over time, focusing on the impact of the COVID-19 pandemic. Panel A shows the logarithm of the number of visitors per month, while Panel B shows the logarithm of the median travel distance to branches. Panels A.1 and B.1 correspond to large banks, and Panels A.2 and B.2 correspond to small banks. The x-axis represents months, and the y-axis represents the estimated coefficients (β_m) with 90% confidence intervals, capturing the differential effect of branch location in sophisticated zip codes on usage metrics, relative to the omitted base month (January 2019).

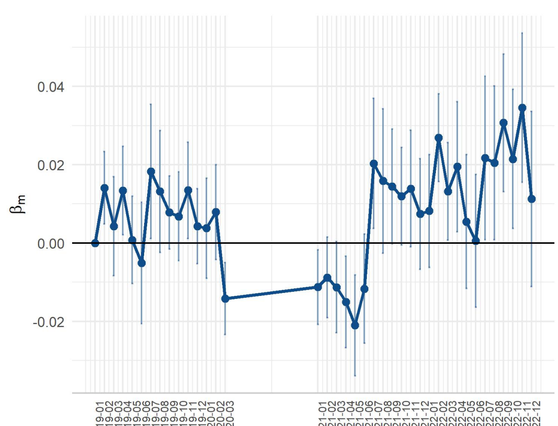
Panel A.1: Large Banks



Panel A.2: Small Banks



Panel B.1: Large Banks



Panel B.2: Small Banks

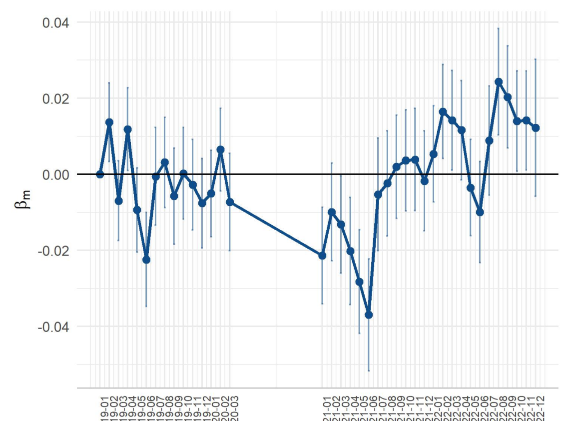
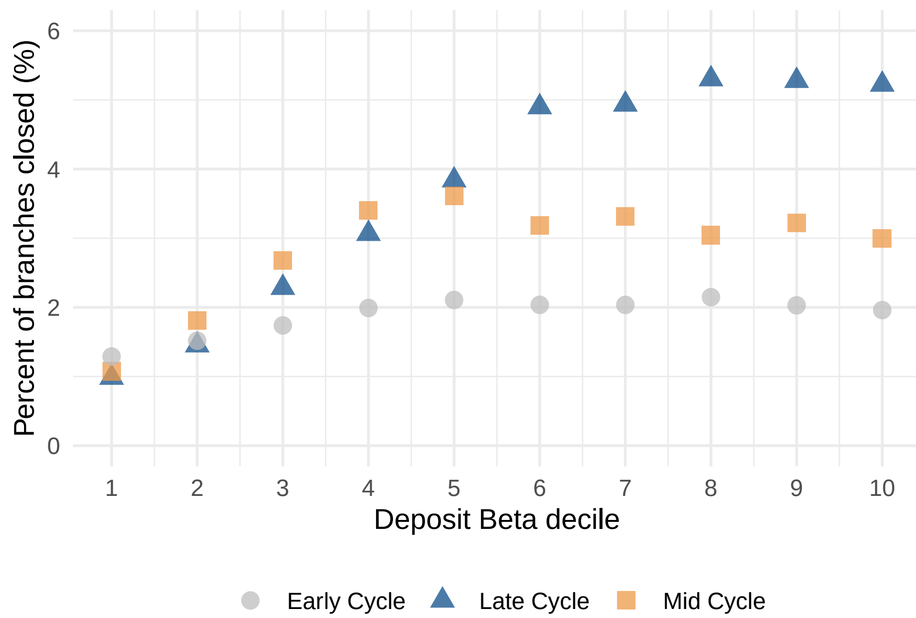


Figure 6: Deposit Beta and Branch Closure

This figure presents the percentage of branches closed by decile of deposit beta value across three interest rate cycles. Panel A shows closures by decile of predicted branch-level beta. Panel B shows closures by decile of actual bank-level beta. Each point represents the average branch closure rate within a given beta decile. The figure includes data for the Early cycle (gray circles), Mid cycle (orange triangles), and Late cycle (blue squares). Beta deciles are constructed separately for each cycle, with lower deciles corresponding to lower beta values.

Panel A: Branch-Level



Panel B: Bank-Level

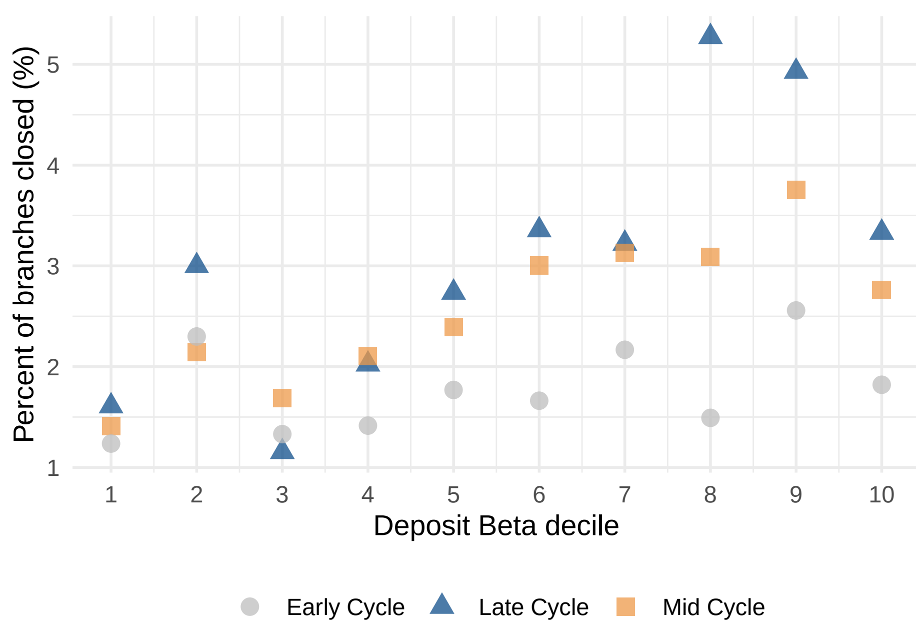


Table 4: Descriptive Statistics for Branch Closure Sample

This table presents summary statistics for branch-level data in 2012 and 2019 for the branch closure sample, disaggregated by bank size. Panel A reports data for large banks (>$100 billion in assets), and Panel B reports data for small banks (<$100 billion). For each year and variable, the table shows the number of observations, mean, standard deviation (SD), and selected percentiles.

Panel A: Large Banks

	Year 2019 (Obs = 33,810)					Year 2012 (Obs = 39,308)				
Variable	Mean	SD	SD (within)	P10	P90	Mean	SD	SD (within)	P10	P90
Closed	0.04	0.19		0.00	0.00	0.02	0.15		0.00	0.00
Deposit Beta	0.25	0.03	0.019	0.21	0.29	0.30	0.03	0.013	0.26	0.34
log(Deposits)	11.22	1.05	0.903	10.12	12.32	10.69	1.11	0.992	9.54	11.83
Acq. branch/presence	0.00	0.07		0.00	0.00	0.02	0.12		0.00	0.00
Branch owned 3plus years	0.98	0.16		1.00	1.00	0.81	0.39		0.00	1.00
Deposit 3yr growth	0.05	0.03		0.01	0.09	0.09	0.08		0.00	0.20
CRA 3yr growth	0.04	0.06		-0.02	0.11	-0.11	0.05		-0.16	-0.06
Establishments 3yr growth	0.01	0.01		-0.00	0.03	-0.01	0.01		-0.02	0.00
Low to Moderate Income Area	0.31	0.15		0.10	0.50	0.30	0.15		0.10	0.48
Mortgage 3yr growth	0.04	0.07		-0.04	0.12	0.01	0.09		-0.09	0.15
Payroll 3yr growth	0.04	0.02		0.02	0.07	-0.00	0.02		-0.02	0.02
Population density (1k km)	0.39	0.26		0.04	0.69	0.36	0.25		0.04	0.66

Panel B: Small Banks

	Year 2019 (Obs = 44,071)					Year 2012 (Obs = 49,309)				
Variable	Mean	SD	SD (within)	P10	P90	Mean	SD	SD (within)	P10	P90
Closed	0.02	0.14		0.00	0.00	0.02	0.15		0.00	0.00
Deposit Beta	0.20	0.04	0.014	0.15	0.25	0.23	0.04	0.010	0.17	0.28
log(Deposits)	10.56	1.26	0.963	9.22	11.87	10.23	1.28	0.972	8.88	11.58
Acq. branch/presence	0.01	0.10		0.00	0.00	0.01	0.09		0.00	0.00
Branch owned 3plus years	0.90	0.30		1.00	1.00	0.89	0.31		0.00	1.00
Deposit 3yr growth	0.04	0.03		0.00	0.08	0.08	0.07		0.00	0.17
CRA 3yr growth	0.05	0.12		-0.04	0.16	-0.10	0.07		-0.17	-0.03
Establishments 3yr growth	0.01	0.01		-0.01	0.02	-0.01	0.01		-0.02	0.00
Low to Moderate Income Area	0.26	0.17		0.00	0.48	0.26	0.17		0.00	0.47
Mortgage 3yr growth	0.04	0.07		-0.04	0.12	0.00	0.08		-0.09	0.10
Payroll 3yr growth	0.04	0.03		0.00	0.07	0.00	0.03		-0.02	0.03
Population density (1k km)	0.21	0.25		0.01	0.69	0.21	0.24		0.01	0.66

Table 5: Descriptive Statistics for Branch Opening Sample

This table presents summary statistics for branch-level data in 2012 and 2019 for the branch opening sample, disaggregated by bank size. Panel A reports data for large banks (>$100 billion in assets), and Panel B reports data for small banks (<$100 billion). For each year and variable, the table shows the number of observations, mean, standard deviation (SD), and selected percentiles.

Panel A: Large Banks

	Year 2019 (Obs = 78,361)					Year 2012 (Obs = 72,396)				
Variable	Mean	SD	SD (within)	P10	P90	Mean	SD	SD (within)	P10	P90
New Entry	0.140	3.680		0.000	0.000	0.340	5.860		0.000	0.000
Deposit Beta	0.230	0.030	0.019	0.200	0.270	0.290	0.040	0.012	0.250	0.340
log(Zip Deposits)	9.960	4.720	3.468	0.690	13.890	10.080	4.170	2.921	0.690	13.520
CRA 3yr growth	0.050	0.080		-0.020	0.120	-0.110	0.050		-0.160	-0.050
Deposit 3yr growth	0.050	0.030		0.010	0.080	0.090	0.080		0.000	0.200
Establishments 3yr growth	0.010	0.010		-0.000	0.030	-0.010	0.010		-0.020	0.000
Low to Moderate Income Area	0.300	0.170		0.070	0.500	0.290	0.170		0.070	0.480
Mortgage 3yr growth	0.050	0.070		-0.040	0.130	0.010	0.090		-0.090	0.140
Payroll 3yr growth	0.040	0.020		0.010	0.070	0.000	0.020		-0.020	0.020

Panel B: Small Banks

	Year 2019 (Obs = 519,855)					Year 2012 (Obs = 623,612)				
Variable	Mean	SD	SD (within)	P10	P90	Mean	SD	SD (within)	P10	P90
New Entry	0.110	3.260		0.000	0.000	0.080	2.880		0.000	0.000
Deposit Beta	0.200	0.040	0.021	0.160	0.250	0.240	0.050	0.014	0.180	0.300
log(Zip Deposits)	10.890	4.280	3.097	0.690	14.230	10.980	3.790	2.641	0.690	13.910
CRA 3yr growth	0.050	0.070		-0.010	0.120	-0.110	0.040		-0.150	-0.060
Deposit 3yr growth	0.050	0.030		0.000	0.080	0.100	0.080		0.010	0.200
Establishments 3yr growth	0.010	0.010		-0.000	0.030	-0.010	0.010		-0.020	0.000
Low to Moderate Income Area	0.310	0.170		0.070	0.500	0.310	0.170		0.070	0.490
Mortgage 3yr growth	0.030	0.060		-0.040	0.110	0.020	0.090		-0.070	0.150
Payroll 3yr growth	0.040	0.020		0.010	0.070	0.000	0.020		-0.020	0.020

Table 6: Baseline Closure Model

This table reports linear probability model estimates from Equation (5a), where the dependent variable equals one if a branch was closed in a given year. Columns 1–2 present estimates for the full sample, while Columns 3–4 and 5–6 report estimates separately for large banks (>$100 billion in assets) and small banks (<$100 billion), respectively. Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Closed=1					
	Full sample		Large banks		Small banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Deposit Beta	0.1286***	0.1700***	0.1719***	0.2586***	0.1007***	0.0966***
	(0.0145)	(0.0213)	(0.0232)	(0.0282)	(0.0127)	(0.0140)
log(Deposits)	-0.0199***	-0.0200***	-0.0231***	-0.0232***	-0.0175***	-0.0175***
	(0.0006)	(0.0007)	(0.0010)	(0.0011)	(0.0005)	(0.0005)
Acq. branch/presence	0.0516***	0.0494***	0.0562***	0.0512***	0.0447***	0.0428***
	(0.0066)	(0.0068)	(0.0108)	(0.0113)	(0.0047)	(0.0046)
Branch owned 3plus years	-0.0055***	-0.0054***	-0.0057*	-0.0068**	-0.0064***	-0.0065***
	(0.0015)	(0.0014)	(0.0030)	(0.0029)	(0.0011)	(0.0011)
log(Bank-County Mortgage Volume)	-0.0003	-0.0006*	-0.0009	-0.0007	-0.0001	-0.0005**
	(0.0003)	(0.0003)	(0.0008)	(0.0015)	(0.0002)	(0.0002)
log(Bank-County CRA Volume)	$-7.86e$-5	-0.0003	0.0006	0.0009	-0.0002	-0.0004*
	(0.0003)	(0.0003)	(0.0005)	(0.0008)	(0.0003)	(0.0003)
Deposit 3yr growth	0.0016		0.0037**		0.0007	
	(0.0010)		(0.0018)		(0.0011)	
Mortgage 3yr growth	-0.0071**		-0.0075		-0.0052**	
	(0.0028)		(0.0049)		(0.0026)	
CRA 3yr growth	-0.0012		-0.0004		-0.0013	
	(0.0008)		(0.0019)		(0.0008)	
Establishments 3yr growth	-0.1332***		-0.2509***		-0.0265	
	(0.0258)		(0.0448)		(0.0180)	
Payroll 3yr growth	-0.0002		-0.0057		0.0053	
	(0.0056)		(0.0100)		(0.0065)	
Low to Moderate Income Area	-0.0040***		-0.0099***		0.0013	
	(0.0015)		(0.0024)		(0.0011)	
State × Year FE	✓		✓		✓	
Bank × Year FE	✓	✓	✓	✓	✓	✓
County × Year FE		✓		✓		✓
Observations	1,592,669	1,592,669	690,038	690,038	902,631	902,631
R^2	0.09844	0.13106	0.05019	0.11084	0.15682	0.21460

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7: Baseline Opening Model

This table presents baseline linear probability model estimates from Equation (5a), where the dependent variable equals one if a branch was opened in a given zip code–year, conditional on the bank not having any branches in that zip code in prior years. Columns 1–2 report estimates for the full sample, while Columns 3–4 and 5–6 present split-sample estimates for large banks (>$100 billion in assets) and small banks (< 1$00 billion), respectively. Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Opening=1					
	Full sample		Large banks		Small banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Deposit Beta	0.0204***	0.0273***	0.0441***	0.0586***	0.0172***	0.0239***
	(0.0017)	(0.0016)	(0.0108)	(0.0108)	(0.0009)	(0.0011)
log(Zip code deposits)	0.0003***	0.0003***	0.0005***	0.0006***	0.0003***	0.0003***
	(1.83*e*-5)	(1.8*e*-5)	(10*e*-5)	(0.0001)	(9.41*e*-6)	(9.79*e*-6)
log(County mortgage volume)	-0.0002		0.0016***		-0.0009***	
	(0.0002)		(0.0005)		(8.51*e*-5)	
log(County CRA volume)	0.0004**		-0.0006*		0.0009***	
	(0.0002)		(0.0003)		(7.22*e*-5)	
Deposit 3yr growth	-0.0003**		0.0009		-0.0005***	
	(0.0001)		(0.0007)		(0.0001)	
Mortgage 3yr growth	0.0003		-0.0059**		0.0015***	
	(0.0006)		(0.0025)		(0.0003)	
CRA 3yr growth	-0.0004		0.0012		-0.0008***	
	(0.0002)		(0.0008)		(0.0002)	
Establishments 3yr growth	0.0279***		0.0428***		0.0238***	
	(0.0023)		(0.0081)		(0.0019)	
Payroll 3yr growth	0.0017**		0.0046		0.0012	
	(0.0007)		(0.0030)		(0.0007)	
Low to Moderate Income Area	-0.0007***		0.0004		-0.0010***	
	(0.0001)		(0.0006)		(0.0001)	
State × Year FE	✓		✓		✓	
Bank × Year FE	✓	✓	✓	✓	✓	✓
County × Year FE		✓		✓		✓
Observations	12,579,759	12,580,951	1,409,902	1,410,042	11,169,857	11,170,909
R^2	0.02837	0.03894	0.01978	0.03866	0.03227	0.04800

Note: *p<0.1; **p<0.05; ***p<0.01

Table 8: Reduced Form Pooled Closure Model

This table presents reduced-form linear probability model estimates of branch closure using Equation (5b), where the dependent variable equals one if a branch was closed in a given year. Panel A reports results for the full sample, and Panel B reports estimates separately for large banks (>$100 billion in assets) and small banks (<$100 billion). The variable *Sophisticated zipcode* is an indicator for whether the branch is located in a sophisticated zip code, defined as a zip code with above-median income, education, and stock market participation. Coefficients of the other control variables are suppressed. Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Full Sample

	Closed=1			
	(1)	(2)	(3)	(4)
College frac	0.0084***	0.0163***		
	(0.0027)	(0.0029)		
Stock market frac	0.0213***	0.0146***		
	(0.0041)	(0.0042)		
Sophisticated zipcode			0.0033***	0.0035***
			(0.0006)	(0.0006)
log(Income)	-0.0041***	-0.0059***	-0.0015***	-0.0024***
	(0.0007)	(0.0008)	(0.0005)	(0.0006)
Age Q1-Q2	0.0011*	0.0011**	0.0010*	0.0012*
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Age Q2-Q3	0.0003	0.0005	0.0009	0.0013*
	(0.0007)	(0.0007)	(0.0008)	(0.0008)
Age >Q3	0.0002	0.0010	0.0019*	0.0029***
	(0.0009)	(0.0009)	(0.0010)	(0.0011)
log(Deposits)	-0.0200***	-0.0201***	-0.0198***	-0.0198***
	(0.0007)	(0.0007)	(0.0006)	(0.0006)
County deposit HHI	-0.0040*		-0.0038	
	(0.0023)		(0.0024)	
Population density	0.0059***		0.0084***	
	(0.0021)		(0.0022)	
Controls	✓	✓	✓	✓
State × Year FE	✓		✓	
Bank × Year FE	✓	✓	✓	✓
County × Year FE		✓		✓
Observations	1,592,670	1,592,670	1,592,670	1,592,670
R^2	0.09853	0.13108	0.09834	0.13090

Note: *p<0.1; **p<0.05; ***p<0.01

Panel B: By Size

	Closed=1							
	Large banks		Small banks		Large banks		Small banks	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
College frac	0.0106**	0.0185***	0.0100***	0.0165***				
	(0.0046)	(0.0048)	(0.0026)	(0.0032)				
Stock market frac	0.0354***	0.0304***	0.0013	-0.0036				
	(0.0049)	(0.0054)	(0.0038)	(0.0043)				
Sophisticated zipcode					0.0058***	0.0061***	0.0009*	0.0014**
					(0.0008)	(0.0007)	(0.0005)	(0.0006)
log(Income)	-0.0075***	-0.0092***	-0.0019***	-0.0037***	-0.0028***	-0.0035***	-0.0004	-0.0017***
	(0.0010)	(0.0013)	(0.0005)	(0.0006)	(0.0008)	(0.0010)	(0.0005)	(0.0005)
Age Q1-Q2	0.0028***	0.0025***	-0.0006	-0.0006	0.0027***	0.0026***	-0.0008*	-0.0007
	(0.0007)	(0.0006)	(0.0005)	(0.0006)	(0.0007)	(0.0006)	(0.0005)	(0.0006)
Age Q2-Q3	0.0022**	0.0021**	-0.0014**	-0.0014**	0.0031***	0.0035***	-0.0015**	-0.0015**
	(0.0009)	(0.0008)	(0.0006)	(0.0007)	(0.0010)	(0.0009)	(0.0006)	(0.0007)
Age >Q3	0.0027**	0.0030**	-0.0019**	-0.0012	0.0060***	0.0068***	-0.0018***	-0.0011
	(0.0013)	(0.0013)	(0.0007)	(0.0009)	(0.0012)	(0.0012)	(0.0007)	(0.0008)
log(Deposits)	-0.0235***	-0.0233***	-0.0174***	-0.0174***	-0.0229***	-0.0227***	-0.0174***	-0.0174***
	(0.0010)	(0.0011)	(0.0005)	(0.0003)	(0.0010)	(0.0010)	(0.0005)	(0.0005)
County deposit HHI	0.0024		-0.0074***		0.0047		-0.0078***	
	(0.0042)		(0.0020)		(0.0043)		(0.0020)	
Population density	0.0034		0.0100***		0.0058		0.0121***	
	(0.0037)		(0.0018)		(0.0039)		(0.0019)	
Controls	✓	✓	✓	✓	✓	✓	✓	✓
State × Year FE	✓		✓		✓		✓	
Bank × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
County × Year FE		✓		✓		✓		✓
Observations	690,261	690,261	904,728	904,728	690,261	690,261	904,728	904,728
R^2	0.05038	0.11067	0.15715	0.21608	0.04998	0.11030	0.15709	0.21602

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 9: Reduced Form Pooled Opening Model

This table presents reduced-form linear probability model estimates of branch opening using Equation (5b), where the dependent variable equals one if a branch was opened in a given zip code–year, conditional on the bank not having any branches in that zip code in prior years. Panel A reports results for the full sample, and Panel B reports estimates separately for large banks (>$100 billion in assets) and small banks (<$100 billion). The variable *Sophisticated zipcode* is an indicator for whether the branch is located in a sophisticated zip code, defined as a zip code with above-median education and stock market participation. Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Full Sample

	Opening=1			
	(1)	(2)	(3)	(4)
College frac	0.0042***	0.0046***		
	(0.0003)	(0.0003)		
Stock market frac	0.0011***	0.0010***		
	(0.0004)	(0.0003)		
Sophisticated zipcode			0.0011***	0.0011***
			(7.21*e*-5)	(7.77*e*-5)
log(Income)	-0.0003***	-0.0003***	0.0002***	0.0002***
	(5.34*e*-5)	(4.26*e*-5)	(5.88*e*-5)	(4.97*e*-5)
Age Q1-Q2	-0.0005***	-0.0004***	-0.0006***	-0.0005***
	(7.62*e*-5)	(7.2*e*-5)	(7.85*e*-5)	(7.54*e*-5)
Age Q2-Q3	-0.0010***	-0.0009***	-0.0010***	-0.0009***
	(9.99*e*-5)	(9.52*e*-5)	(9.66*e*-5)	(9.49*e*-5)
Age >Q3	-0.0014***	-0.0014***	-0.0012***	-0.0012***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
log(Zip code deposits)	0.0003***	0.0003***	0.0003***	0.0003***
	(1.72*e*-5)	(1.7*e*-5)	(1.79*e*-5)	(1.78*e*-5)
County deposit HHI	-0.0015***		-0.0010***	
	(0.0002)		(0.0002)	
Population density	-0.0019***		-0.0013***	
	(0.0004)		(0.0004)	
Controls	✓	✓	✓	✓
Bank × Year FE	✓	✓	✓	✓
State × Year FE	✓		✓	
County × Year FE		✓		✓
Observations	12,579,759	12,580,951	12,579,759	12,580,951
R^2	0.02854	0.03905	0.02837	0.03890

Note: *p<0.1; **p<0.05; ***p<0.01

Panel B: By Size

	Opening=1							
	Large banks		Small banks		Large banks		Small banks	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
College frac	0.0128***	0.0145***	0.0035***	0.0037***				
	(0.0019)	(0.0020)	(0.0002)	(0.0002)				
Stock market frac	0.0009	0.0008	0.0009***	0.0011***				
	(0.0025)	(0.0023)	(0.0002)	(0.0002)				
Sophisticated zipcode					0.0028***	0.0031***	0.0009***	0.0009***
					(0.0004)	(0.0006)	(4.82*e*-5)	(4.83*e*-5)
log(Income)	-0.0004*	-0.0005**	-0.0004***	-0.0004***	0.0007**	0.0008**	3.4*e*-5	8.47*e*-5***
	(0.0002)	(0.0002)	(3.14*e*-5)	(3.47*e*-5)	(0.0003)	(0.0003)	(2.47*e*-5)	(2.93*e*-5)
Age Q1-Q2	-0.0018***	-0.0015***	-0.0003***	-0.0003***	-0.0020***	-0.0017***	-0.0004***	-0.0004***
	(0.0005)	(0.0005)	(4.01*e*-5)	(4.06*e*-5)	(0.0005)	(0.0005)	(4.21*e*-5)	(4.19*e*-5)
Age Q2-Q3	-0.0024***	-0.0023***	-0.0008***	-0.0007***	-0.0025***	-0.0023***	-0.0008***	-0.0007***
	(0.0006)	(0.0007)	(5.56*e*-5)	(5.82*e*-5)	(0.0006)	(0.0006)	(5.89*e*-5)	(6.13*e*-5)
Age >Q3	-0.0033***	-0.0037***	-0.0010***	-0.0011***	-0.0030***	-0.0033***	-0.0009***	-0.0009***
	(0.0007)	(0.0009)	(7.01*e*-5)	(7.33*e*-5)	(0.0006)	(0.0008)	(7.34*e*-5)	(7.47*e*-5)
log(Zip code deposits)	0.0005***	0.0005***	0.0003***	0.0003***	0.0005***	0.0006***	0.0003***	0.0003***
	(9.56*e*-5)	(9.86*e*-5)	(9.11*e*-6)	(9.43*e*-6)	(0.0001)	(0.0001)	(9.3*e*-6)	(9.7*e*-6)
County deposit HHI	0.0002		-0.0015***		0.0012		-0.0010***	
	(0.0009)		(0.0002)		(0.0009)		(0.0002)	
Population density	0.0019		-0.0030***		0.0036**		-0.0025***	
	(0.0015)		(0.0002)		(0.0015)		(0.0002)	
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Bank × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
State × Year FE	✓		✓		✓		✓	
County × Year FE		✓		✓		✓		✓
Observations	1,409,902	1,410,042	11,169,857	11,170,909	1,409,902	1,410,042	11,169,857	11,170,909
R^2	0.02047	0.03918	0.03243	0.04808	0.02009	0.03883	0.03235	0.04799

Note: *p<0.1; **p<0.05; ***p<0.01

Table 10: Closures by Regime

This table presents linear probability model estimates of branch closure using Equation (5a), where the dependent variable equals one if a branch was closed in a given year. Panel A reports results for large banks (>\$100 billion in assets), and Panel B reports results for small banks (<\$100 billion). Each column corresponds to a distinct time period: 2001–2007, 2008–2011, 2012–2019, and 2020–2023. Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Large Banks

	Closed=1							
	2001:2007		2008:2011		2012:2019		2020:2023	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Deposit Beta	0.1457***	0.1894***	0.2629***	0.2619***	0.1604***	0.2270***	0.2257***	0.3918***
	(0.0250)	(0.0335)	(0.0435)	(0.0480)	(0.0399)	(0.0454)	(0.0358)	(0.0460)
log(Deposits)	-0.0186***	-0.0189***	-0.0177***	-0.0176***	-0.0243***	-0.0242***	-0.0337***	-0.0341***
	(0.0025)	(0.0025)	(0.0029)	(0.0030)	(0.0021)	(0.0022)	(0.0037)	(0.0037)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
State × Year FE	✓		✓		✓		✓	
Bank × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
County × Year FE		✓		✓		✓		✓
Observations	142,385	142,385	132,325	132,325	292,360	292,360	122,968	122,968
R^2	0.04676	0.10429	0.03751	0.08816	0.04365	0.10800	0.05419	0.11451

Note: *p<0.1; **p<0.05; ***p<0.01

Panel B: Small Banks

	Closed=1							
	2001:2007		2008:2011		2012:2019		2020:2023	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Deposit Beta	0.0839***	0.1145***	0.1947***	0.1624***	0.1027***	0.1087***	0.0879***	0.0592***
	(0.0218)	(0.0304)	(0.0329)	(0.0429)	(0.0220)	(0.0234)	(0.0177)	(0.0213)
log(Deposits)	-0.0132***	-0.0131***	-0.0175***	-0.0176***	-0.0187***	-0.0186***	-0.0204***	-0.0202***
	(0.0007)	(0.0007)	(0.0009)	(0.0009)	(0.0008)	(0.0007)	(0.0010)	(0.0010)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
State × Year FE	✓		✓		✓		✓	
Bank × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
County × Year FE		✓		✓		✓		✓
Observations	219,922	219,922	163,599	163,599	355,372	355,372	163,738	163,738
R^2	0.17050	0.24294	0.17226	0.22562	0.15609	0.21143	0.13485	0.19031

Note: *p<0.1; **p<0.05; ***p<0.01

Table 11: Openings by Regime

This table presents linear probability model estimates of branch openings using Equation (5a), where the dependent variable equals one if a new branch was opened in the given zipcode-year. Panel A reports results for large banks (>$100 billion in assets), and Panel B reports results for small banks (<$100 billion). Each column corresponds to a distinct time period: 2001–2007, 2008–2011, 2012–2019, and 2020–2023. Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Large Banks

	Opening=1							
	2001:2007		2008:2011		2012:2019		2020:2023	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Deposit Beta	0.1754***	0.1888***	0.1223***	0.1344***	0.0387***	0.0452***	0.0356**	0.0312*
	(0.0324)	(0.0366)	(0.0297)	(0.0312)	(0.0090)	(0.0120)	(0.0174)	(0.0157)
log(Zip code deposits)	0.0010***	0.0011***	0.0011***	0.0011***	0.0002***	0.0002***	0.0004**	0.0004**
	(8.57*e*-5)	(0.0001)	(0.0002)	(0.0002)	(5.9*e*-5)	(6.06*e*-5)	(0.0002)	(0.0002)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
State × Year FE	✓		✓		✓		✓	
Bank × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
County × Year FE		✓		✓		✓		✓
Observations	275,851	275,874	237,712	237,729	597,698	597,796	298,641	298,643
R^2	0.01996	0.04397	0.02747	0.04348	0.00914	0.02054	0.01361	0.03102

Note: *p<0.1; **p<0.05; ***p<0.01

Panel B: Small Banks

	Opening=1							
	2001:2007		2008:2011		2012:2019		2020:2023	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Deposit Beta	0.0461***	0.0553***	0.0248***	0.0305***	0.0199***	0.0245***	0.0045***	0.0068***
	(0.0035)	(0.0035)	(0.0021)	(0.0023)	(0.0013)	(0.0015)	(0.0007)	(0.0009)
log(Zip code deposits)	0.0005***	0.0005***	0.0003***	0.0003***	0.0002***	0.0002***	0.0002***	0.0002***
	(2.04*e*-5)	(2.06*e*-5)	(2.22*e*-5)	(2.32*e*-5)	(6.5*e*-6)	(6.87*e*-6)	(8.3*e*-6)	(9.29*e*-6)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
State × Year FE	✓		✓		✓		✓	
Bank × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
County × Year FE		✓		✓		✓		✓
Observations	3,177,348	3,177,627	2,250,395	2,250,459	3,981,622	3,982,318	1,760,492	1,760,505
R^2	0.03789	0.05492	0.03103	0.04609	0.02392	0.03776	0.02157	0.03549

Note: *p<0.1; **p<0.05; ***p<0.01

Table 12: Closures - With Usage Controls

This table presents linear probability model estimates of branch closure using Equation (5c), where the dependent variable equals one if a branch was closed in a given year. Panel A reports results for the full sample, and Panel B reports estimates separately for large banks (>$100 billion in assets) and small banks (<$100 billion). The models include measures of branch usage: the percentage drop in visits from 2019 to 2021 and the log of the average distance (in kilometers) traveled by customers to the branch in 2019. Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A

	Closed=1			
	Full sample			
	(1)	(2)	(3)	(4)
Deposit Beta	0.1281***	0.1322***	0.0874***	0.0781***
	(0.0213)	(0.0284)	(0.0184)	(0.0243)
log(Deposits)	-0.0187***	-0.0189***	-0.0192***	-0.0194***
	(0.0023)	(0.0024)	(0.0024)	(0.0024)
Drop in visits			0.0101***	0.0083**
			(0.0027)	(0.0037)
log(Distance km)			0.0078***	0.0111***
			(0.0018)	(0.0022)
Controls	✓	✓	✓	✓
State × Year FE	✓		✓	
Bank × Year FE	✓	✓	✓	✓
County × Year FE		✓		✓
Observations	131,462	131,462	131,257	131,257
R^2	0.06144	0.09128	0.06219	0.09209

Note: *p<0.1; **p<0.05; ***p<0.01

Panel B

	Closed=1							
	Large banks				Small banks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Deposit Beta	0.1793***	0.2378***	0.1053***	0.1156***	0.0827***	0.0573**	0.0583***	0.0406
	(0.0277)	(0.0379)	(0.0264)	(0.0388)	(0.0227)	(0.0291)	(0.0222)	(0.0288)
log(Deposits)	-0.0249***	-0.0247***	-0.0262***	-0.0263***	-0.0143***	-0.0140***	-0.0144***	-0.0142***
	(0.0047)	(0.0048)	(0.0047)	(0.0048)	(0.0009)	(0.0010)	(0.0009)	(0.0010)
Drop in visits			0.0116	0.0143			0.0090***	0.0055***
			(0.0078)	(0.0099)			(0.0016)	(0.0020)
log(Distance km)			0.0164***	0.0205***			0.0014	0.0040**
			(0.0027)	(0.0035)			(0.0013)	(0.0017)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
State × Year FE	✓		✓				✓	
Bank × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
County × Year FE		✓		✓	✓	✓		✓
Observations	58,459	58,459	58,432	58,432	73,003	73,003	72,825	72,825
R^2	0.03228	0.09030	0.03382	0.09201	0.10932	0.16491	0.10988	0.16540

Note: *p<0.1; **p<0.05; ***p<0.01

Table 13: Openings - With Usage Controls

This table presents linear probability model estimates of branch opening using Equation (5c), where the dependent variable equals one if a branch was opened in a given zip code–year, conditional on the bank not having any branches in that zip code in prior years. Panel A reports results for the full sample, and Panel B reports estimates separately for large banks (>$100 billion in assets) and small banks (<$100 billion). The models include measures of branch usage: the percentage drop in visits from 2019 to 2021 and the log of the average distance (in kilometers) traveled by customers to the branch in 2019. Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A

	Opening=1			
	Full sample			
	(1)	(2)	(3)	(4)
Deposit Beta	0.0058***	0.0068***	0.0050**	0.0065***
	(0.0021)	(0.0020)	(0.0020)	(0.0020)
log(Zip code deposits)	0.0008***	0.0008***	0.0008***	0.0008***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Drop in visits			0.0009***	0.0010***
			(0.0003)	(0.0003)
log(Distance km)			2.19e-5	-0.0001
			(0.0001)	(0.0001)
Controls	✓	✓	✓	✓
Bank × Year FE	✓	✓	✓	✓
State × Year FE	✓		✓	
County × Year FE		✓		✓
Observations	824,821	824,821	823,003	823,003
R^2	0.02563	0.04022	0.02578	0.04037

Note: *p<0.1; **p<0.05; ***p<0.01

Panel B

	Opening=1							
	Large banks				Small banks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Deposit Beta	0.0308**	0.0275**	0.0282**	0.0261*	0.0019	0.0042***	0.0012	0.0040***
	(0.0124)	(0.0132)	(0.0112)	(0.0130)	(0.0012)	(0.0014)	(0.0012)	(0.0014)
log(Zip code deposits)	0.0019**	0.0020**	0.0018**	0.0020**	0.0006***	0.0007***	0.0006***	0.0006***
	(0.0008)	(0.0009)	(0.0008)	(0.0009)	(4.2e-5)	(4.49e-5)	(4.1e-5)	(4.42e-5)
Drop in visits			0.0019	0.0018			0.0007***	0.0008***
			(0.0015)	(0.0015)			(0.0001)	(0.0002)
log(Distance km)			0.0004	0.0001			3.29e-5	$-8.77e$-5
			(0.0005)	(0.0007)			(8.49e-5)	(9.56e-5)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Bank × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
State × Year FE	✓		✓		✓		✓	
County × Year FE		✓		✓		✓		✓
Observations	112,960	112,960	112,540	112,540	711,861	711,861	710,463	710,463
R^2	0.01587	0.04090	0.01606	0.04110	0.03189	0.05181	0.03206	0.05196

Note: *p<0.1; **p<0.05; ***p<0.01

Internet Appendix: The Decline of Branch Banking

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Table IA.1: Baseline Closure Model - Version 2

This table reports linear probability model estimates from Equation (5a), where the dependent variable equals one if a branch was closed in a given year. Columns 1–2 present estimates for the full sample, while Columns 3–4 and 5–6 report estimates separately for large banks (>$100 billion in assets) and small banks (<$100 billion), respectively. The primary independent variable is deposit franchise (DF) per dollar. Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Closed=1					
	Full sample		Large banks		Small banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Deposit Beta	0.1222***	0.1638***	0.1648***	0.2514***	0.0946***	0.0911***
	(0.0143)	(0.0210)	(0.0229)	(0.0280)	(0.0129)	(0.0141)
Openings by other banks	0.0026***	0.0022***	0.0032***	0.0027***	0.0023***	0.0019***
	(0.0004)	(0.0004)	(0.0006)	(0.0007)	(0.0005)	(0.0006)
log(Deposits)	-0.0199***	-0.0201***	-0.0232***	-0.0233***	-0.0175***	-0.0175***
	(0.0006)	(0.0007)	(0.0010)	(0.0011)	(0.0005)	(0.0005)
Acq. branch/presence	0.0514***	0.0492***	0.0559***	0.0510***	0.0445***	0.0426***
	(0.0066)	(0.0068)	(0.0108)	(0.0113)	(0.0047)	(0.0047)
Branch owned 3plus years	-0.0055***	-0.0055***	-0.0057*	-0.0068**	-0.0064***	-0.0065***
	(0.0015)	(0.0014)	(0.0030)	(0.0029)	(0.0011)	(0.0011)
log(Bank-County Mortgage Volume)	-0.0003	-0.0006*	-0.0009	-0.0006	-0.0001	-0.0005**
	(0.0003)	(0.0003)	(0.0008)	(0.0015)	(0.0002)	(0.0002)
log(Bank-County CRA Volume)	-8.09×10^{-5}	-0.0003	0.0006	0.0009	-0.0002	-0.0004*
	(0.0003)	(0.0003)	(0.0005)	(0.0008)	(0.0003)	(0.0003)
Deposit 3yr growth	0.0015		0.0035*		0.0007	
	(0.0010)		(0.0018)		(0.0011)	
Mortgage 3yr growth	-0.0071**		-0.0075		-0.0052**	
	(0.0028)		(0.0049)		(0.0026)	
CRA 3yr growth	-0.0012		-0.0004		-0.0012	
	(0.0008)		(0.0018)		(0.0008)	
Establishments 3yr growth	-0.1390***		-0.2588***		-0.0310*	
	(0.0261)		(0.0452)		(0.0180)	
Payroll 3yr growth	-0.0006		-0.0061		0.0050	
	(0.0057)		(0.0100)		(0.0065)	
Low to Moderate Income Area	-0.0039**		-0.0098***		0.0013	
	(0.0015)		(0.0024)		(0.0011)	
State × Year FE	✓		✓		✓	
Bank × Year FE	✓	✓	✓	✓	✓	✓
County × Year FE		✓		✓		✓
Observations	1,592,669	1,592,669	690,038	690,038	902,631	902,631
R^2	0.09847	0.13108	0.05024	0.11087	0.15685	0.21461

Note: *p<0.1; **p<0.05; ***p<0.01

Table IA.2: Baseline Opening Model - Version 2

This table presents baseline linear probability model estimates from Equation (5a), where the dependent variable equals one if a branch was opened in a given zip code–year, conditional on the bank not having any branches in that zip code in prior years. Columns 1–2 report estimates for the full sample, while Columns 3–4 and 5–6 present split-sample estimates for large banks (>$100 billion in assets) and small banks (< 1$00 billion), respectively. The primary independent variable is deposit franchise (DF) per dollar, which captures the predicted deposit franchise value. Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Opening=1					
	Full sample		Large banks		Small banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Deposit Beta	0.0186***	0.0253***	0.0414***	0.0558***	0.0155***	0.0221***
	(0.0016)	(0.0015)	(0.0103)	(0.0104)	(0.0009)	(0.0010)
Closures by other banks	0.0014***	0.0014***	0.0029***	0.0028***	0.0013***	0.0013***
	(9.53×10^{-5})	(9.19×10^{-5})	(0.0007)	(0.0007)	(6.46×10^{-5})	(6.34×10^{-5})
log(Zip code deposits)	0.0003***	0.0003***	0.0005***	0.0005***	0.0003***	0.0003***
	(1.67×10^{-5})	(1.64×10^{-5})	(8.75×10^{-5})	(9.23×10^{-5})	(8.54×10^{-6})	(8.9×10^{-6})
Deposit 3yr growth	-0.0003**		0.0009		-0.0005***	
	(0.0001)		(0.0007)		(0.0001)	
Mortgage 3yr growth	0.0004		-0.0058**		0.0015***	
	(0.0006)		(0.0024)		(0.0003)	
CRA 3yr growth	-0.0004*		0.0012		-0.0008***	
	(0.0002)		(0.0008)		(0.0002)	
log(lag County Mortgage Vol)	-0.0003		0.0016***		-0.0010***	
	(0.0002)		(0.0005)		(8.54×10^{-5})	
log(lag County CRA Vol)	0.0004**		-0.0006*		0.0009***	
	(0.0002)		(0.0003)		(7.22×10^{-5})	
Establishments 3yr growth	0.0276***		0.0430***		0.0235***	
	(0.0023)		(0.0081)		(0.0019)	
Payroll 3yr growth	0.0019**		0.0050		0.0014*	
	(0.0008)		(0.0030)		(0.0007)	
Low to Moderate Income Area	-0.0006***		0.0004		-0.0009***	
	(0.0001)		(0.0006)		(0.0001)	
State × Year FE	✓		✓		✓	
Bank × Year FE	✓	✓	✓	✓	✓	✓
County × Year FE		✓		✓		✓
Observations	12,579,759	12,580,951	1,409,902	1,410,042	11,169,857	11,170,909
R^2	0.02850	0.03906	0.02001	0.03886	0.03240	0.04812

Note: *p<0.1; **p<0.05; ***p<0.01

Table IA.3: Baseline Opening Model - Version 4

This table presents baseline linear probability model estimates from Equation (5a), where the dependent variable equals one if a branch was opened in a given zip code–year, conditional on the bank not having any branches in that zip code in prior years. The sample includes only zip codes from CBSAs in which a given bank owned at least one branch in the prior year. Columns 1–2 report estimates for the full sample, while Columns 3–4 and 5–6 present split-sample estimates for large banks (>$100 billion in assets) and small banks (<$100 billion), respectively. The primary independent variable is deposit franchise (DF) per dollar, which captures the predicted deposit franchise value. Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Opening=1					
	Full sample		Large banks		Small banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Deposit Beta	0.0207***	0.0275***	0.0445***	0.0598***	0.0174***	0.0240***
	(0.0017)	(0.0016)	(0.0106)	(0.0109)	(0.0009)	(0.0011)
log(Zip code deposits)	0.0003***	0.0003***	0.0005***	0.0006***	0.0003***	0.0003***
	(1.84×10^{-5})	(1.8×10^{-5})	(0.0001)	(0.0001)	(9.4×10^{-6})	(9.67×10^{-6})
Deposit 3yr growth	-0.0003**		0.0009		-0.0005***	
	(0.0001)		(0.0007)		(0.0001)	
Mortgage 3yr growth	0.0005		-0.0053**		0.0015***	
	(0.0005)		(0.0022)		(0.0003)	
CRA 3yr growth	-0.0003		0.0015*		-0.0008***	
	(0.0002)		(0.0008)		(0.0002)	
log(lag County Mortgage Vol)	-0.0002		0.0017***		-0.0010***	
	(0.0002)		(0.0005)		(9.09×10^{-5})	
log(lag County CRA Vol)	0.0004**		-0.0007*		0.0009***	
	(0.0002)		(0.0003)		(7.7×10^{-5})	
Establishments 3yr growth	0.0281***		0.0406***		0.0241***	
	(0.0024)		(0.0084)		(0.0019)	
Payroll 3yr growth	0.0011		0.0016		0.0009	
	(0.0008)		(0.0028)		(0.0008)	
Low to Moderate Income Area	-0.0007***		0.0005		-0.0009***	
	(0.0001)		(0.0007)		(0.0001)	
State × Year FE	✓		✓		✓	
Bank × Year FE	✓	✓	✓	✓	✓	✓
County × Year FE		✓		✓		✓
Observations	10,720,601	10,721,616	1,201,496	1,201,613	9,519,105	9,520,003
R^2	0.03137	0.04319	0.02026	0.04118	0.03612	0.05376

Note: *p<0.1; **p<0.05; ***p<0.01

Table IA.4: Usage

This table reports regression estimates from Equation (3), examining branch usage and customer travel distance to branches. Results are shown separately for large banks (≥$100 billion in assets) and small banks (<$100 billion in assets). Panel A presents estimates from a parsimonious model using a single indicator for sophisticated zip codes. Panel B reports estimates using separate demographic variables, including age quartiles, income, education, and stock market participation. Columns 1–2 report regressions where the dependent variable is branch usage, defined as the percentage drop in visits from 2019 to 2021 for each branch. Columns 3–4 use the mean distance (in kilometers) that customers traveled to visit the branch in 2019 as the dependent variable. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A

	Drop in visits		log(distance km)	
	Large banks	Small banks	Large banks	Small banks
	(1)	(2)	(3)	(4)
Sophisticated zipcode	0.0652***	0.1034***	0.1841***	0.1212***
	(0.0099)	(0.0077)	(0.0187)	(0.0092)
Age Q1-Q2	-0.0200***	-0.0410***	-0.0661***	-0.0440***
	(0.0043)	(0.0080)	(0.0122)	(0.0099)
Age Q2-Q3	-0.0703***	-0.1039***	-0.0795***	-0.0515***
	(0.0076)	(0.0094)	(0.0204)	(0.0127)
Age >Q3	-0.0710***	-0.1264***	0.0280	0.0888***
	(0.0113)	(0.0124)	(0.0247)	(0.0168)
log(Income)	0.0053	0.0093**	-0.0698***	-0.0354***
	(0.0042)	(0.0043)	(0.0084)	(0.0051)
log(Deposits)	0.0185***	0.0278***	0.0291**	-0.0129**
	(0.0064)	(0.0040)	(0.0115)	(0.0057)
Population density	0.3688***	0.5439***	-0.3718***	-0.1433**
	(0.0405)	(0.0248)	(0.0282)	(0.0556)
Bank FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Observations	26,521	26,276	26,560	26,355
R^2	0.26680	0.43095	0.19958	0.33392

Note: *p<0.1; **p<0.05; ***p<0.01

Panel B

	Drop in visits		log(distance km)	
	Large banks	Small banks	Large banks	Small banks
	(1)	(2)	(3)	(4)
College frac	0.4153***	0.4414***	0.4255***	0.1894***
	(0.0312)	(0.0318)	(0.0352)	(0.0465)
Stock market frac	0.0001	0.1851***	0.8185***	0.8561***
	(0.0281)	(0.0368)	(0.0703)	(0.0656)
Age Q1-Q2	-0.0381***	-0.0528***	-0.0455***	-0.0166
	(0.0042)	(0.0082)	(0.0095)	(0.0103)
Age Q2-Q3	-0.1025***	-0.1275***	-0.1011***	-0.0474***
	(0.0094)	(0.0098)	(0.0194)	(0.0126)
Age >Q3	-0.1156***	-0.1541***	-0.0560	0.0693***
	(0.0121)	(0.0124)	(0.0334)	(0.0169)
log(Income)	-0.0286***	-0.0139***	-0.1154***	-0.0509***
	(0.0046)	(0.0049)	(0.0076)	(0.0056)
log(Deposits)	0.0127*	0.0252***	0.0071	-0.0186***
	(0.0067)	(0.0038)	(0.0123)	(0.0055)
Population density	0.3058***	0.4568***	-0.4754***	-0.2577***
	(0.0353)	(0.0229)	(0.0293)	(0.0539)
Bank FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Observations	26,521	26,276	26,560	26,355
R^2	0.28	0.44	0.26	0.36

Note: *p<0.1; **p<0.05; ***p<0.01