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THE DECLINE OF BANK BRANCHING

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ABSTRACT

We study U.S. bank branch openings and closings from 2001 to 2023. Both are more common in areas with low deposit franchise value, a consequence of greater interest-rate sensitivity among financially sophisticated households with higher digital banking adoption. The effects are strongest for large banks. Lending plays a minimal role. Incumbents retain branches where depositors are less sensitive to rates because they can extract deposit spreads; entrants avoid such markets because sticky customers are difficult to attract. The pandemic accelerated closures by increasing digital reliance. Our findings highlight deposit franchise value as the primary driver of modern branch restructuring.

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Introduction

This paper examines the drivers of bank branch opening and closure decisions during the industry restructuring period from 2001 to 2023. We show that measures of local financial sophistication strongly predict both outcomes, as depositors in these areas exhibit greater interest-rate sensitivity, 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. 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)). Figure 1 shows that 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.

This paper shows that bank branch restructuring has largely been driven by variation in the value of the deposit franchise—the ability of banks to retain deposits priced at interest rates *below* the prevailing market rate. Our regressions provide weak evidence that lending or local loan demand explains bank restructuring. Unlike deposits, neither local growth in mortgage originations nor local growth in small business loan originations has consistent explanatory power for branch openings and closings. We argue that the primary driver of restructuring today is technology, which reduces both deposit market power and the non-pecuniary benefits of proximity to a branch. This stands in contrast to earlier periods, where deregulation was the main driver of restructuring. Thus, our paper contributes to explaining the recent decline in bank branch networks and the broader restructuring of the banking industry.

For incumbent banks (i.e., those who may close branches), our empirical design exploits variation in deposit and lending conditions across each bank's pre-existing branch network. For each branch owned by a given bank, we first construct a measure of the value of that branch's deposits. The measure follows Drechsler, Savov, and Schnabl (2023) and estimates the bank-level present value of rents generated per dollar of bank deposits (the "Deposit Franchise Value," or DF). We adapt their approach by constructing a bank-level predicted rate sensitivity measure using average local demographic characteristics. We then use this relationship to predict each branch's DF based on its geographic location. This strategy provides variation in branch-level deposit valuation *within each bank*. With the branch-based DF measure, we can understand how a given bank decides which of its branches to close as a function of the marginal profit each branch contributes based on the characteristics of the local depositor base. Put differently, we estimate all our branch closure models with bank (and bank-time) fixed effects.

For potential entering banks, we construct a set of candidate zip codes for each bank consisting of all zip codes located within CBSA areas where the bank owns at least one branch in the prior period, as well as all zip codes located in CBSAs where the bank 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 franchise (DF) measure described above, which in this context reflects the DF a bank would expect to earn if it were to enter the zip code by opening a new branch.

We use our indirect approach because direct information on deposit pricing at the branch level is not available systematically. Some recent research has used deposit quote data from RateWatch, but these data are only meaningful for a small subset of branches ("rate setting branches"). Using RateWatch even for the rate-setters, as argued by Begenau and Stafford (2023), is problematic as a measure of local pricing power because many large banks extend the same (quoted) rate over a large region. Moreover, branches designated as 'rate-setters' are almost never closed. Our strategy instead begins with a model that explains the *overall* bank-level deposit-cost sensitivity–defined as the change in interest expenses on deposits / total deposits during each of the past three interest-rate cycles–as a function of local demographic variables (e.g., age, income, education, and rates of stock market participation) assigned to each bank by averaging across the local demographics near the bank's branch footprint. This preliminary model provides coefficients, which we then use to build a predicted *branch-level* measure of deposit price sensitivity ("Deposit β") using the demographic variables associated with people living in the zip code of each branch. The predicted DF (which depends on β) varies across branches within each bank; two branches located very close to each other (e.g., within the same zip code) would be assigned the same franchise value, but a bank owning branches in different zip codes would have different franchise values, with the degree of difference depending on the variation in the demographic factors across the two areas.

Our location-based deposit franchise (DF) measure strongly predicts both branch closures and openings, but operates differently across the two margins. Incumbent banks are less likely to close branches in high-DF areas, where depositors are relatively insensitive to interest rates and thus more profitable to retain. In contrast, potential entrants are less likely to open branches in these same areas, as low rate sensitivity makes depositors harder to attract from incumbents. These patterns help explain why the industry has been—and will likely continue to be—reshaped. The widespread adoption of phone and internet banking reduces frictions associated with geographic distance and weakens banks' local pricing power over deposits (Haendler, 2022; Jiang, Yu, and Zhang, 2022; Koont, 2023). Consistent with this, we find that 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—resulting in lower DF. We further document that individuals in these areas visit branches less frequently and travel greater distances when they do—reducing the strategic value of maintaining a physical presence.

We also find that the marginal impact of the deposit franchise on closures increases sharply after the COVID-19 pandemic. The pandemic was a 'teachable moment' for many people, who learned that technology can effectively substitute for physical proximity. Work at home became prevalent, and this change forced many to rearrange their lives in ways that emphasized online rather than in-person interactions. Richer, more educated, and younger people made these adjustments more than others, and this shows up in the impact of the demographic drivers of the DF. In fact, we show a decline in the average value of deposits in the later interest rate cycle (2022-2024) compared to the earlier one (2016-2019), with a larger decline at big banks and in areas with high population densities.

The relationship between DF 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 respond more systematically to variation in DF 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 and thus generate lower DF.

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. Similarly, d'Avernas, Eisfeldt, Huang, Stanton, and Wallace (2023) find that large banks serve clientele who demand a broader set of financial services beyond deposit-taking. 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.

In contrast to the DF, 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 from 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.[1] As such, physical proximity no longer matters much for information production.[2] 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).[3]

[1] 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).

[2] 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)

[3] 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

In the last part of our analysis, we use cell phone mobility data to track the usage of bank branches, focusing on the decline in the number of visitors around the Pandemic, as well as the distance those visitors travel to visit a branch. These metrics help predict bank branch closures but are less helpful in explaining openings. Adding them to our model attenuates the impact of the value of the deposit franchise itself only slightly, and it continues to exhibit strong explanatory power. This occurs, we show, because both branch usage and the DF are strongly correlated, as both are driven by local demographics. These findings close the loop on our core argument: areas with sophisticated residents substitute away from brick-and-mortar banking and into technology. This behavior reduces the value of their deposits to banks because customer facility with technology increases their interest-rate sensitivity, and because technology reduces the amenity value to customers of close proximity to a bank branch. People who rely mainly on mobile apps and the internet to access their bank do not value a nearby branch. As a result, demographic variables drive all three outcomes: branch usage, the DF (which depends mainly on interest-rate sensitivity), and 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 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

instead arguing that the physical distance between banks (or bankers) and borrowers matters much less than in the past.

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, ours is the first paper to model bank closure and opening decisions separately, rather than focus on the *net* change in bank branches within specific localities. Our results underscore the value of this approach, as incumbents and potential entrants face fundamentally opposed incentives. For incumbents, areas with high DF (low interest-rate sensitive customers) are attractive because they can extract rents from 'sticky' customers by pricing deposits well below market rates. Such areas, however, are not attractive to potential entrants, since sticky customers are hard to draw away from the incumbents. Our results imply that the DF (which, again, depends on the deposit β) is a much better measure of local market power than the traditional metric based on concentration (HHI). High DF represents two factors which reinforce market power: 1) incumbent banks are able to exploit rate-insensitive people (this is the channel emphasized by Drechsler, Savov, and Schnabl (2017)); and, 2) high DF reflects high entry barriers because potential-entrant banks know they will have a hard time drawing deposits away from incumbents.

Our paper also contributes to the large literature emphasizing how the location and scope of bank branching has mediated the supply and flow of capital within and across local markets. Until recently the literature has spoken with one voice: the ownership and location of branches introduces substantial frictions in banking services, both on the deposit and lending sides. Areas with highly concentrated ownership of branches experienced less competition in both deposit and lending markets. Closure of branches reduced local small business lending (Nguyen (2019)). Moreover, the flow of capital across markets was affected by connections between local areas from branch ownership networks (Gilje, Loutskina, and Strahan, 2016; Cortés and Strahan, 2017). The most powerful evidence of the importance of bank branching emerged from studies of deregulation of restrictions on the ownership of bank branches both 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 deposit and credit services increased. The decline in branching in the past decade, our results suggest, has occurred because these frictions are being eroded by information technology, which makes distance and physical proximity between banks and their customers increasingly irrelevant. As such, the competition-enhancing benefits which followed declines in branch-based frictions from deregulation ought to continue from the advent and penetration of information technology.

1. A Framework to Understand Branch Restructuring

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 → Changes in the branch-level Deposit Franchise Value
- Local Demographics → Changes in Usage of Branches
- Low DF and Low Branch Usage → More Branch Closures
- Low DF and High Potential Branch Usage → More Branch Openings

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 (DF). 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 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 the DF at the bank level, and then use that model to compute DF at the branch level; 2) we then estimate how demographics affect branch usage based on cell phone data; 3) we estimate how DF 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.[4] 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 are made publicly available. These "Call Reports" provide a breakdown of balance sheets and income statements.

[4]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.

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 The Deposit Franchise (DF)

3.1. Bank-Level Deposit Franchise and Its Determinants

We follow Drechsler et al. (2023), who construct a simple measure of bank's deposit franchise value, 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).[5] We follow Drechsler et al. (2023) in assuming that banks set their deposit rate equal to a fixed fraction of the market rate (so, $r_i^d = \beta_i \times r^f$), and that banks with different depositor clientele and banks operating in markets with different levels of competition will optimally choose different deposit betas. Also following Drechsler et al. (2023), we assume deposits run off equally in each year over the next 10 years. With these assumptions, the DF for bank i is given by:

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

where $\beta_i = \Delta r_i^d / \Delta r^f$, r_i^d is the interest expense on deposits per dollar of deposits, r^f is the Fed Funds rate, and r^p is the the long-term interest rate, which is assumed to be 2.5%.

[5] The DSS framework does not capture value created by expectations of future deposit growth. Since banks would clearly care about growth, we capture this effect (crudely) by including past growth of total deposits (as well as small business loans and mortgages) into our closure models.

In our application, we set c (the annual operating cost per dollar of deposits) to zero, as we do not have good ways to capture the annual per-dollar operating costs associated with each branch. To the extent that these costs are similar across branches for each bank, they would have no effect on our closure model because we estimate all of our effects within bank (and year). In other words, the costs would be absorbed by the bank-year fixed effects. Consistent with this claim, Narayanan and Ratnadiwakara (2024) show no relationship between customer demographics and bank non-interest expenses (a rough measure of c).

We estimate DF_i per dollar of deposits across the last three monetary tightening cycles, using bank-level realizations of β_i: first for the 2004–2006 cycle, second for the 2016–2019 cycle, and third for the 2022–2024 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_i 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 2004-2006 cycle, 2.5% in the 2016-2019 cycle, and 4% during 2022-2023). We use just the increasing portion of each rate cycle. The end of both the 2004-2006 and 2016-2019 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.[6] The sample period in the second 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

[6]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.

the amount of deposits each bank holds in each of its branches.[7] These regressions are structured, as follows:

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

where i 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 ($HHI_{i,t}$), where markets are defined at the county level. The other control variables include bank-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 / assets, plus a constant. 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 0.34.[8] Large banks operate in areas with younger, more educated, wealthier populations that have higher rates of stock market

[7]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.

[8]In principle, one could build an analogous metric based on loan-market pricing power. However, Call Report 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, as we describe below we use quantity-based measures of local lending conditions from both the mortgage markets and the market for loans to small businesses.

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 deposit franchise (DF) values (Panel A), split by the three monetary tightening cycles and by bank size. Large banks have lower DF on average in all three cycles (recall Table 2) because they have higher βs, 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). Banks have higher pricing power in areas with higher income. 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 0.021 (=0.16 x 0.15) in the third cycle, for example. While market concentration (HHI) enters both models negatively (suggesting greater bank pricing power in more concentrated areas), its effects lose statistical significance in the third cycle. In contrast, local population density – which itself is strongly correlated with HHI - has a large impact which increases in importance over time. Large banks also exhibit much higher βs than small, and this effect also increases in the last cycle.[9]

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

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

in the last two cycles relative to the first. For context, a bank raising all of its deposits in areas with financially sophisticated depositors would have 2%-3% lower present-value of profits generated from each dollar of deposits, compared to a bank raising all of its deposits in areas with less-sophisticated depositors.

3.2. Predicted Deposit Franchise Values at the Branch Level

We construct branch-level measures of the DF by applying the coefficients from Equation (2) to each bank's branches using the demographic measures from each branch's zip code (opposed to the average across all branches, as in Equation (2)). We use the coefficients from the first interest-rate cycle for the years 2001-2014, from the second cycle for 2015-2019, and the coefficients from the third cycle for the years 2020-2023.[10] Since banks own branches in zip codes with different demographic factors, this procedure generates within-bank variation in the value of the deposit franchise.

Panel B of Figure 3 shows the distribution of predicted deposit franchise values 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 branch-level differences over time is illustrated in Figure 4, which compares predicted DF values across interest rate cycles. Panels A and B plot branch-level predicted DF for the 2016–2019 vs. 2022–2024 and 2004–2006 vs. 2016–2019 cycles, respectively. Panels C and D show the same comparisons using actual bank-level DF. As expected, the cross-section of DF is highly correlated over time, with a tighter relationship at the branch level. This reflects the stability of both the explanatory variables (de-

[10]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.

mographics change slowly) and the coefficient estimates, as documented in Table 2. Put simply, branches with above-average DF early in the sample tend to remain high-DF in later years. The figure also shows that DF values are generally lower in the post-pandemic period, as the regression line falls below the 45-degree line. Between the second and third cycles, the fitted line rotates downward 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 DF 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:

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

where b indexes banks, j indexes branches, k indexes the demographic variables observed in each branch j's zip code.[11] The control variables include a bank fixed effect, state fixed effect, the county-level population density, and the log total deposits held in branch j.

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.[12] The number of visits, for example, drop 6 percentage points more at large-bank 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:

[11] 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.

[12] 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.

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

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 *Drop in 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 consistently they travel further when they do visit 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 deposit franchise value (DF) and branch usage, with more financially sophisticated areas exhibiting lower DF 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 DF 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 DF (Panel A) or the bank-level actual DF (Panel B). The pattern is clear—particularly during the second and third cycles: branches with lower franchise value 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 low-DF branches, compared to less than 2 percent for those with high DF.[13]

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 the deposit franchise value. Since the data structure differs between openings and closings, we describe each in turn:

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 b was closed in year t:

$$\text{Closure}_{b,j,t} = \gamma DF_{b,j,t} + \text{Other controls} + \text{Fixed effects} + \varepsilon_{b,j,t} \tag{5a}$$

In (5a), $DF_{b,j,t}$ equals the predicted value of the deposit franchise for branch j owned by bank b 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. 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.

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

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.

For control variables, we include the lagged log level of deposits, the three-year past growth rate of (i) deposits, (ii) mortgage applications and (iii) small business loan originations to capture local supply and demand conditions for deposits and loans. County-level growth in the number of establishments and payroll serves capture local economic growth. We also control for county-level population density. 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. 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.[14]

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). Since potential entrants have no deposits 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 franchise (DF) metric with the underlying demographic and market concentration variables that were used to construct it. The regression specification is as follows:

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

Here, $D_{b,j,t}^k$ represents the k-th demographic variable at branch j owned by bank b and time t. Fixed effects again include *bank* $\times$ *year* and *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.

[14]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.

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.[15] 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. 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.[16]

[15] 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.

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

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 DF 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 and county 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. Small banks exhibit faster lending growth to small businesses. 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 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), higher DF 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 the DF (≈ 0.004 for large banks and 0.003 for small banks), for example, leads to a decline in annual branch closure probability of about 0.4 percentage points (column 4). This effect is large, equal to about 10% of the unconditional mean closure rate (=4% per year for the large banks) during our sample. Beyond the DF, which captures the per-dollar value of the current stock of deposits, higher levels of deposits in the branch from the preceding year also has strong power to predict branch closures for large banks. Hence the value of both "deposits in place" seems to drive closure decisions.

In contrast, neither the growth in market-level deposits nor loans (mortgage and small business loans) has much ability to explain branch closures. We do find a marginally significant effect of small business lending growth on smaller banks' branch closures, but none for larger ones. This contrast 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).[17]

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 plays a central role in predicting entry. Higher DF—reflecting lower interest-rate sensitivity among local

[17]In the Internet Appendix, we report enhanced models with two additional measures of local lending: one based on the log of small-business loan originations in the bank-county-year, and the other based on the log of mortgage originations by bank-county-year. As with local lending growth, these bank-specific measures have weak statistical relationships to bank closures (and openings), with inconsistent sign patterns across samples and specifications.

[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.

depositors—is associated with reduced entry. A one-standard-deviation increase in DF (approximately 0.004 for large banks and 0.0045 for small banks, after removing variation explained by fixed effects) lowers the probability of opening a branch by 0.12% (=0.004 x -0.3, from column (4)), or about 30% of the unconditional opening rate of 0.42%.[19] Local deposit levels and economic growth also enter strongly, with the expected sign: more deposits and faster establishment growth increase the likelihood of entry, opposite to what we observe for closures. The economic magnitude of the level of deposits is similar to that of DF. Hence, banks enter new markets which are 'rich' in deposits, but only when price sensitivity is high (DF is low).[20]

Taken together, the opening and closure results show that low values of DF predict both a higher likelihood of exit by incumbent banks and a greater probability of entry by new banks.[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 DF plays a key role in driving branch restructuring decisions. Comparing these results with those from Table 2, we see that high levels of financial sophistication lead to lower DF (higher deposit beta), and higher rates of both branch openings and closings. Younger populations are also strongly

[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.

[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.

associated with lower DF (higher beta) and more entry (Table 8). 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 low deposit franchise value are consistently most likely to be closed, with the marginal effect of the DF increasing over time. The effects are largest after the Pandemic. For large banks, a standard-deviation decline in the deposit franchise (=0.006) comes with an increase in closure probability of more than one percentage point (column (8)), equal to about one-quarter of the unconditional closure rate. As in the baseline model, openings are also consistently higher in areas with low DF, both across the four regimes 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 is 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 customare 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

[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.

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 slightly attenuates the effect of the DF on closure, from –0.89 to –0.63 for large banks (Table 12, Panel B, columns (3) and (4)). 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.

The effects of usage on openings are less clear, however. Like closures, DF continues to correlate negatively 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 lowers both the DF (by raising 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.

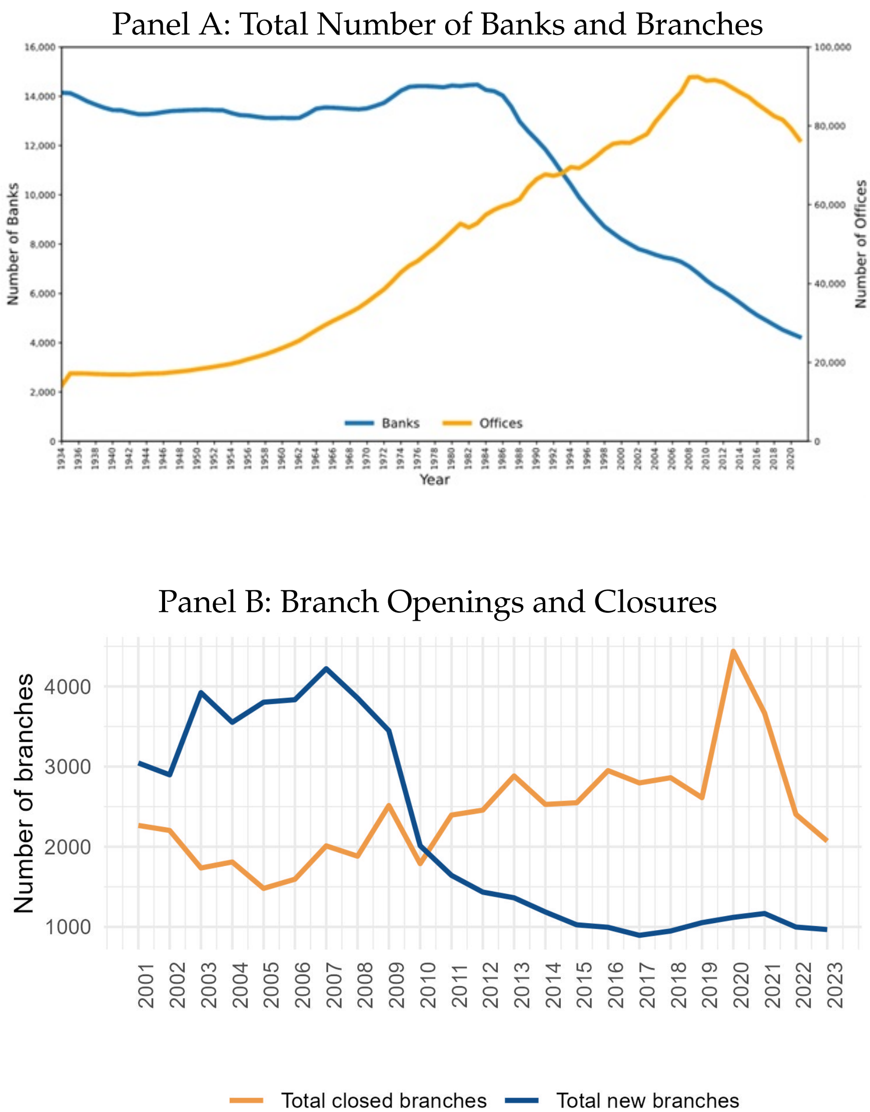
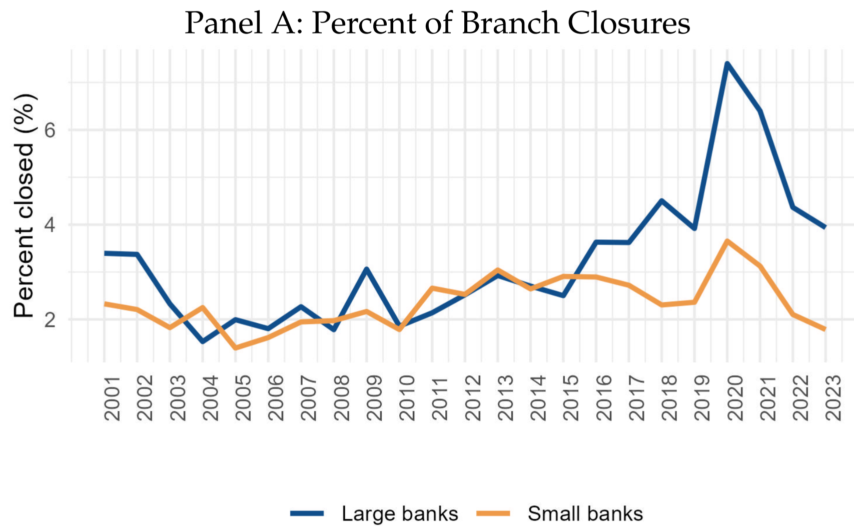


Figure 2: Percent of Openings and Closures

This figure presents the annual percentage of branches closed and opened by large banks ($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.



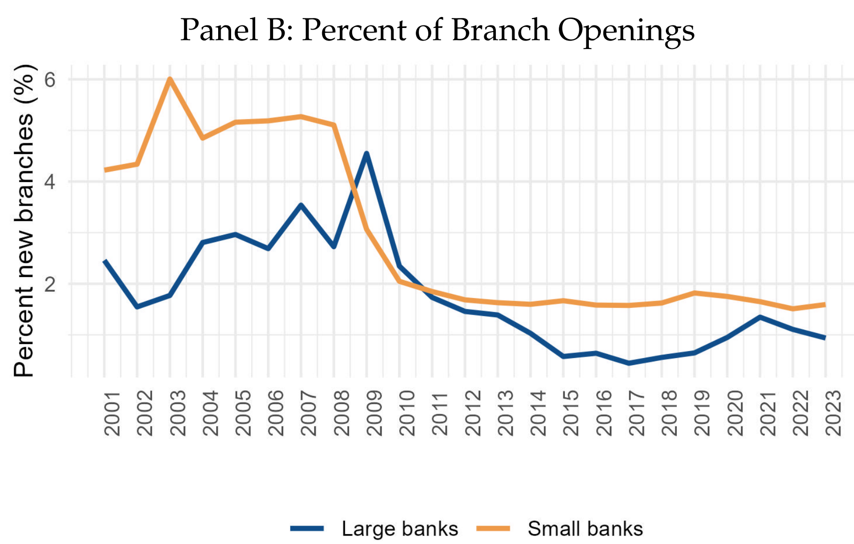


Table 1: Descriptive Statistics - Bank Level

This table presents summary statistics for the bank-level samples during three interest rate cycles, separately for large banks ($100 billion in assets) and small banks. Panels A, B, and C correspond to the 2022–2024, 2015–2019, and 2004–2006 cycles, respectively. For each group, the table reports the mean, standard deviation (SD), and selected percentiles for variables.

Panel A: 2022-2024 Cycle

	Large Banks (Obs = 27)				Small Banks (Obs = 4,296)			
Variable	Mean	SD	P10	P90	Mean	SD	P10	P90
Age	37.29	2.91	34.35	39.78	40.76	4.29	35.67	45.72
College educated fraction	0.53	0.16	0.38	0.79	0.29	0.14	0.16	0.48
Deposit-weighted Pop. density	0.48	0.16	0.26	0.68	0.14	0.21	0.01	0.55
Deposit beta	0.34	0.15	0.18	0.57	0.18	0.12	0.04	0.35
Family income (000)	85.59	40.08	57.80	106.60	57.95	18.04	39.00	80.00
Frac. deposits in sophisticated zipcodes	0.75	0.26	0.47	1.00	0.45	0.41	0.00	1.00
HHI	0.26	0.16	0.16	0.37	0.23	0.13	0.11	0.39
Stock market participation frac	0.30	0.12	0.18	0.40	0.20	0.08	0.10	0.29

Panel B: 2015-2019 Cycle

	Large Banks (Obs = 38)				Small Banks (Obs = 4,872)			
Variable	Mean	SD	P10	P90	Mean	SD	P10	P90
Age	37.72	2.82	34.21	40.93	40.76	4.30	35.68	45.73
College educated fraction	0.54	0.15	0.41	0.76	0.30	0.14	0.16	0.50
Deposit-weighted Pop. density	0.49	0.15	0.28	0.66	0.15	0.21	0.01	0.57
Deposit beta	0.24	0.11	0.14	0.39	0.17	0.12	0.02	0.34
Family income (000)	85.39	31.17	58.10	117.30	58.80	18.72	40.00	82.00
Frac. deposits in sophisticated zipcodes	0.78	0.24	0.52	1.00	0.46	0.41	0.00	1.00
HHI	0.24	0.17	0.12	0.32	0.23	0.13	0.11	0.38
Stock market participation frac	0.30	0.11	0.18	0.43	0.20	0.09	0.10	0.30

Panel C: 2004-2006 Cycle

	Large Banks (Obs = 32)				Small Banks (Obs = 5,515)			
Variable	Mean	SD	P10	P90	Mean	SD	P10	P90
Age	37.65	2.36	34.31	39.54	39.91	4.31	34.82	45.29
College educated fraction	0.51	0.13	0.38	0.72	0.26	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	0.10	0.10	0.37
Family income (000)	70.97	23.76	48.00	90.70	50.23	15.20	35.00	69.00
Frac. deposits in sophisticated zipcodes	0.76	0.20	0.54	1.00	0.44	0.41	0.00	1.00
HHI	0.21	0.11	0.14	0.27	0.23	0.13	0.11	0.39
Stock market participation frac	0.29	0.10	0.22	0.39	0.20	0.08	0.11	0.29

Table 2: Bank-Level Deposit Beta

This table presents regression estimates of deposit beta from Equation (2) across three interest rate cycles: 2004–2006, 2016–2019, and 2022–2024. 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.

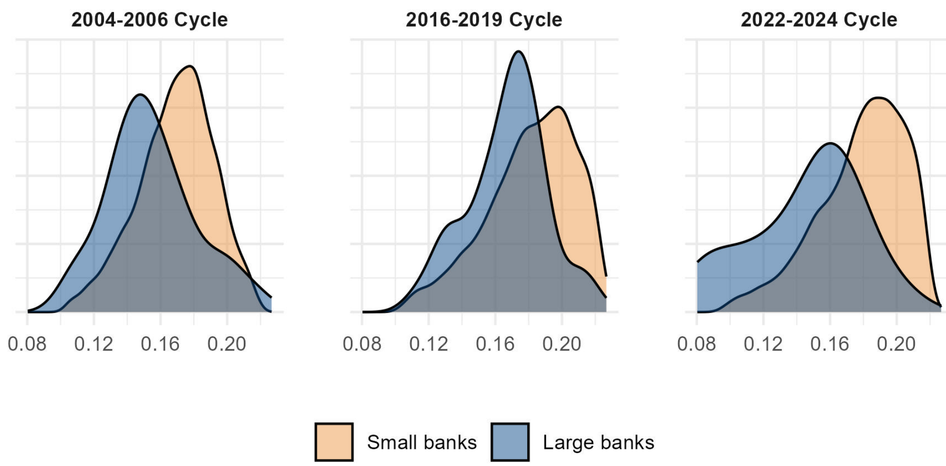
	Deposit Beta					
	2004-2006	2016-2019	2022-2024	2004-2006	2016-2019	2022-2024
	(1)	(2)	(3)	(4)	(5)	(6)
Frac of deposits in sophisticated zipcodes				0.0225***	0.0301***	0.0270***
				(0.0040)	(0.0052)	(0.0052)
College frac	0.1645***	0.1440***	0.1468***			
	(0.0207)	(0.0258)	(0.0267)			
Stock market frac	0.0051	0.0870**	0.0512			
	(0.0285)	(0.0352)	(0.0368)			
Age Q1-Q2	-0.0090**	0.0019	-0.0046	-0.0120***	0.0008	-0.0058
	(0.0037)	(0.0045)	(0.0045)	(0.0036)	(0.0044)	(0.0044)
Age Q2-Q3	-0.0197***	0.0013	-0.0075	-0.0230***	0.0011	-0.0084*
	(0.0042)	(0.0051)	(0.0052)	(0.0040)	(0.0049)	(0.0049)
Age >Q3	-0.0127**	-0.0218***	-0.0326***	-0.0151***	-0.0191***	-0.0316***
	(0.0053)	(0.0073)	(0.0074)	(0.0049)	(0.0069)	(0.0070)
log(Income)	-0.0444***	-0.0384***	-0.0244**	-0.0250***	-0.0083	0.0006
	(0.0076)	(0.0099)	(0.0099)	(0.0067)	(0.0085)	(0.0085)
County deposit HHI	-0.0254**	-0.0254*	-0.0209	-0.0237**	-0.0213	-0.0194
	(0.0113)	(0.0139)	(0.0139)	(0.0114)	(0.0140)	(0.0140)
log(Assets)	0.0122***	0.0044***	0.0148***	0.0138***	0.0058***	0.0160***
	(0.0012)	(0.0014)	(0.0013)	(0.0012)	(0.0014)	(0.0013)
Population density	0.0175*	0.0517***	0.0646***	0.0584***	0.0903***	0.1023***
	(0.0102)	(0.0121)	(0.0123)	(0.0089)	(0.0105)	(0.0106)
Transaction deposits/Assets	-0.1211***	-0.1149***	-0.1094***	-0.1222***	-0.1137***	-0.1094***
	(0.0198)	(0.0208)	(0.0199)	(0.0199)	(0.0209)	(0.0200)
Constant	0.5406***	0.4877***	0.2278**	0.3438***	0.1819**	-0.0242
	(0.0816)	(0.1058)	(0.1064)	(0.0735)	(0.0928)	(0.0929)
Observations	5,539	4,910	4,323	5,539	4,910	4,323
R^2	0.11	0.10	0.18	0.10	0.09	0.17

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

Figure 3: Deposit Franchise Value per Dollar of Deposits

This figure presents density plots of deposit beta (DF) values across three interest rate cycles: 2004–2006, 2016–2019, and 2022–2024. Panel A displays bank-level DF distributions, while Panel B displays predicted branch-level DF distributions. In both panels, small banks (assets $<$ \$100 billion) are shown in orange, and large banks (assets $>$ \$100 billion) are shown in blue. Each subplot represents the distribution of DF values during the indicated interest rate cycle.

Panel A: Bank-Level



Panel B: Branch-Level

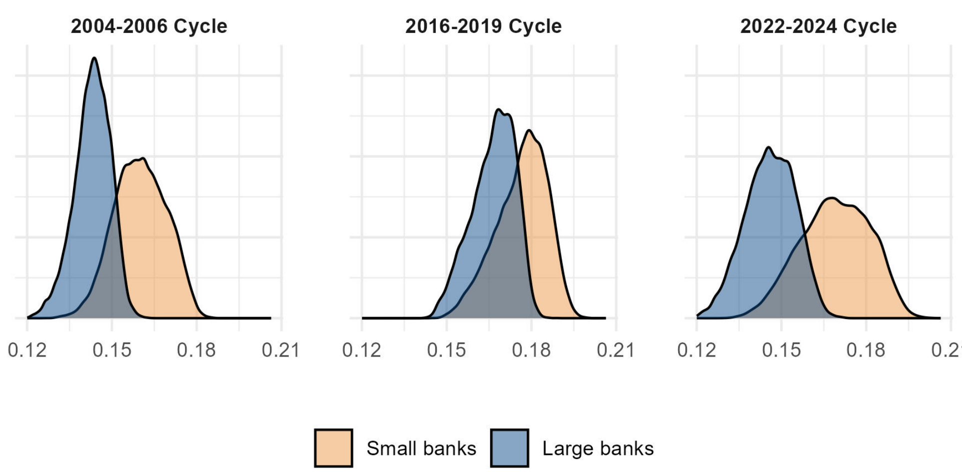


Figure 4: Deposit Franchise Correlations Across Cycles

This figure presents scatter plots comparing deposit franchise (DF) values per dollar between pairs of interest rate cycles. 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 $>$ \$100 billion, blue). The x-axis reports DF per dollar in the earlier cycle, and the y-axis reports DF per dollar in the later cycle. The dashed line denotes the 45-degree reference line. The solid line represents the fitted relationship from a linear regression.

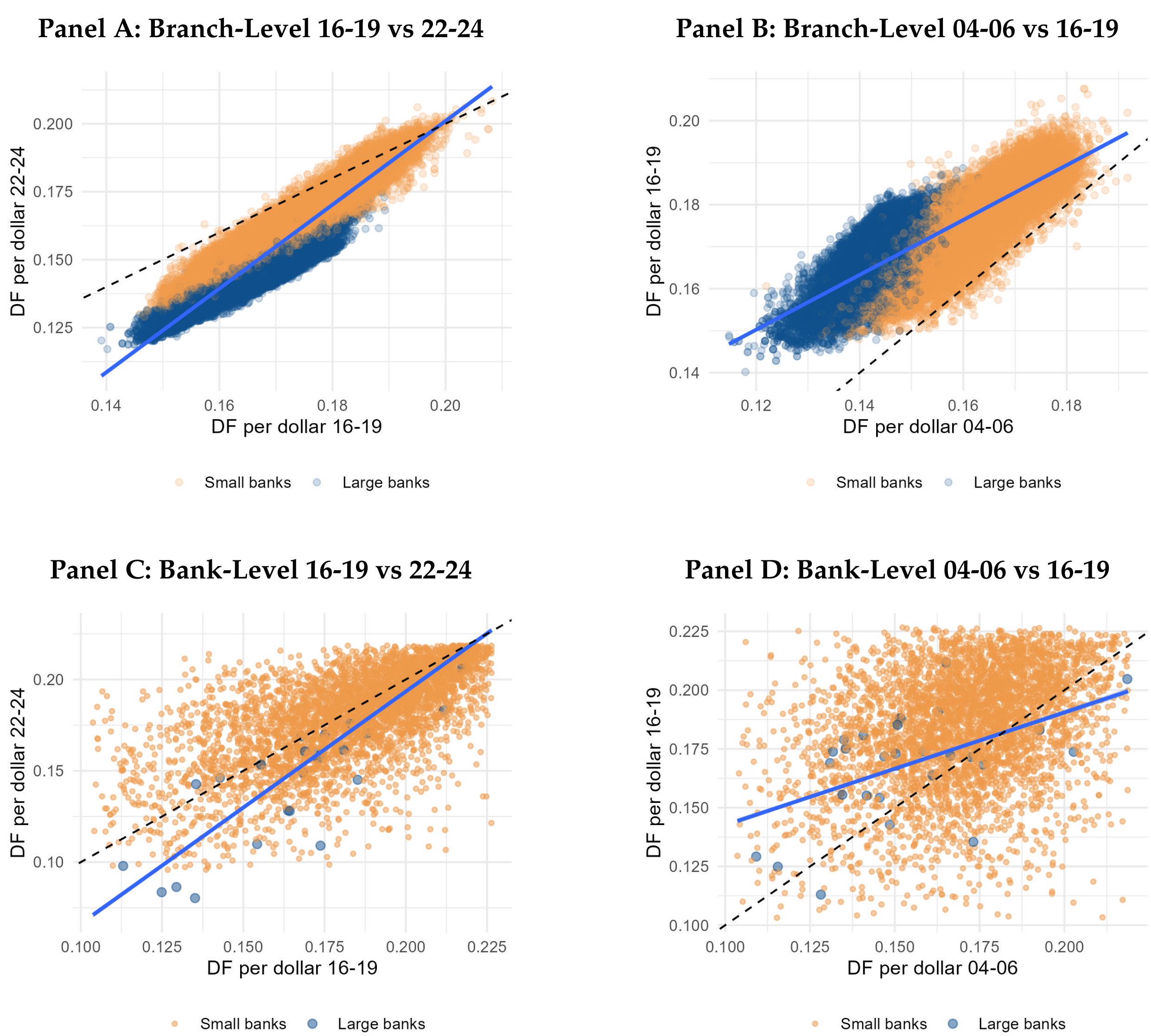


Table 3: Usage

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

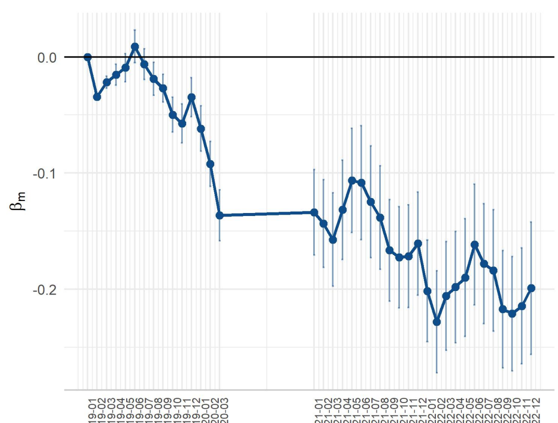
	Drop in visits		log(distance km)	
	Large banks	Small banks	Large banks	Small banks
	(1)	(2)	(3)	(4)
College frac	0.4153***	0.4414***	0.4255***	0.1894***
	(0.0312)	(0.0318)	(0.0352)	(0.0465)
Stock market frac	0.0001	0.1851***	0.8185***	0.8561***
	(0.0281)	(0.0368)	(0.0703)	(0.0656)
Age Q1-Q2	-0.0381***	-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: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

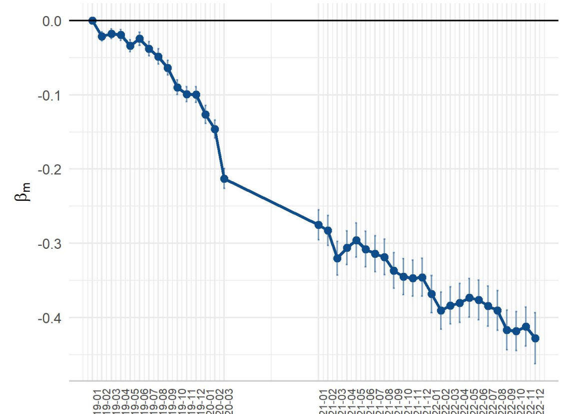
Figure 5: Dynamic Branch Usage

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).

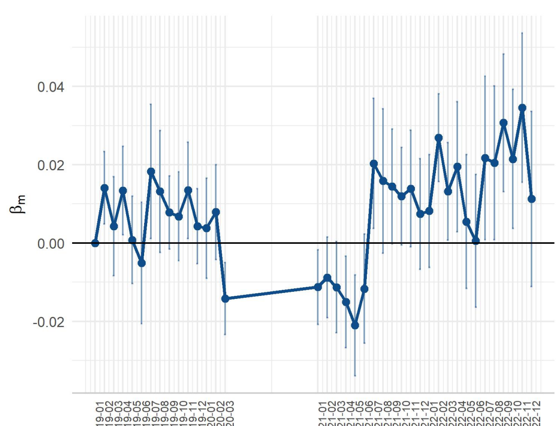
Panel A.1: Large Banks



Panel A.2: Small Banks



Panel B.1: Large Banks



Panel B.2: Small Banks

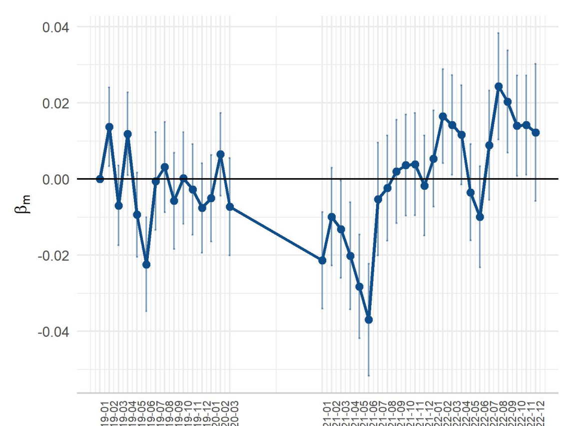
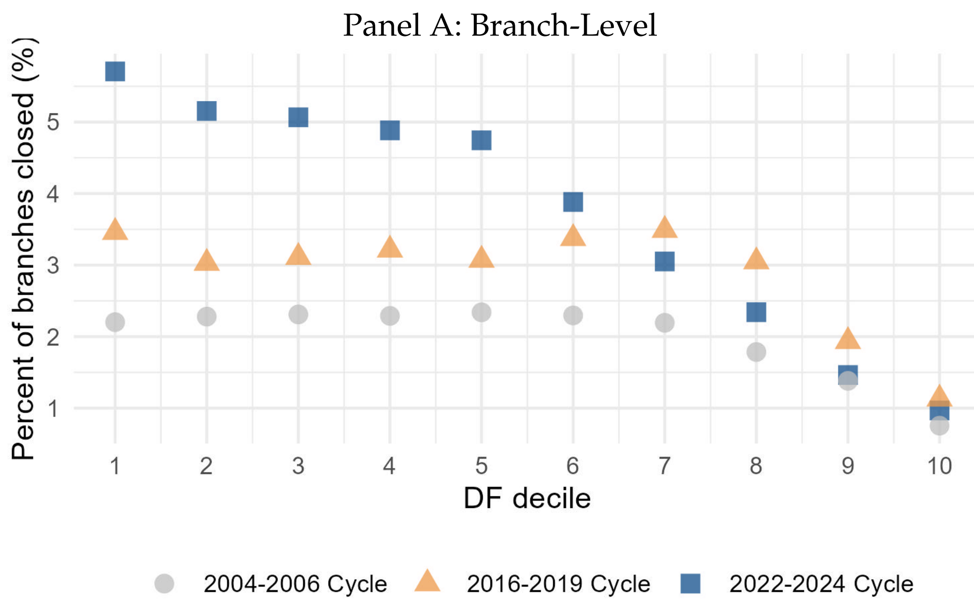


Figure 6: Deposit Franchise and Branch Closure

This figure presents the percentage of branches closed by decile of deposit franchise (DF) value across three interest rate cycles. Panel A shows closures by decile of predicted branch-level DF. Panel B shows closures by decile of actual bank-level DF. Each point represents the average branch closure rate within a given DF decile. The figure includes data for the 2004–2006 cycle (gray circles), 2016–2019 cycle (orange triangles), and 2022–2024 cycle (blue squares). DF deciles are constructed separately for each cycle, with lower deciles corresponding to lower DF values.



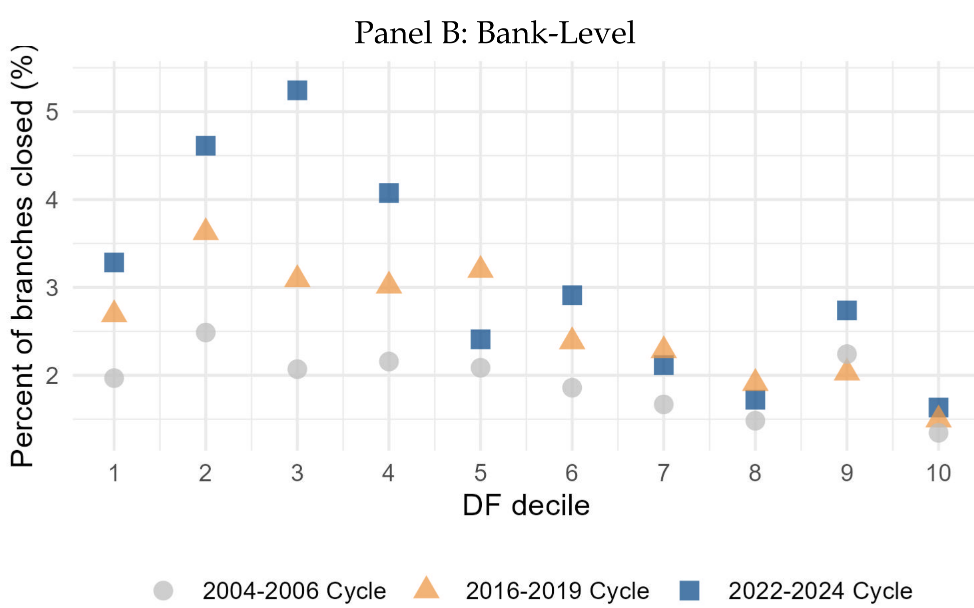


Table 4: Descriptive Statistics for Branch Closure Sample

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				0.02	0.15			
DF per dollar	0.17	0.01	0.0047	0.16	0.18	0.14	0.01	0.0037	0.13	0.15
log(Deposits)	11.16	1.06	0.931	10.05	12.28	10.64	1.12	1.019	9.44	11.81
Acq. branch/presence	0.00	0.07	0.067c	0.00	0.00	0.02	0.12	0.118	0.00	0.00
Branch owned 3plus years	0.98	0.16	0.141	1.00	1.00	0.81	0.39	0.270	0.00	1.00
CRA 3yr growth	0.04	0.06		-0.02	0.11	-0.11	0.05		-0.16	-0.06
Deposit 3yr growth	0.05	0.03		0.01	0.09	0.09	0.08		0.00	0.20
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				0.02	0.15			
DF per dollar	0.18	0.01	0.0035	0.16	0.19	0.16	0.01	0.0022	0.15	0.17
log(Deposits)	10.51	1.23	0.9455	9.13	11.83	10.20	1.25	0.9536	8.80	11.55
Acq. branch/presence	0.01	0.10	0.0928	0.00	0.00	0.01	0.09	0.0829	0.00	0.00
Branch owned 3plus years	0.90	0.30	0.221	1.00	1.00	0.89	0.31	0.186	0.00	1.00
CRA 3yr growth	0.05	0.12		-0.04	0.16	-0.10	0.07		-0.17	-0.03
Deposit 3yr growth	0.04	0.03		0.00	0.08	0.08	0.07		0.00	0.17
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	3.740				0.360	6.020			
DF per dollar	0.17	0.01	0.00452	0.16	0.18	0.15	0.01	0.00369	0.14	0.15
log(Zip Deposits)	10.90	3.96	3.466	0.69	13.99	10.95	3.31	2.923	8.98	13.63
CRA 3yr growth	0.05	0.08		-0.02	0.13	-0.11	0.05		-0.16	-0.05
Deposit 3yr growth	0.05	0.03		0.01	0.08	0.09	0.08		0.00	0.20
Establishments 3yr growth	0.01	0.01		-0.00	0.03	-0.01	0.01		-0.02	0.00
Low to Moderate Income Area	0.30	0.17		0.07	0.50	0.29	0.17		0.06	0.49
Mortgage 3yr growth	0.05	0.07		-0.04	0.13	0.01	0.09		-0.09	0.14
Payroll 3yr growth	0.04	0.02		0.01	0.07	0.00	0.02		-0.02	0.02

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 (%)	0.100	3.200				0.080	2.790			
DF per dollar	0.17	0.01	0.00492	0.16	0.19	0.16	0.01	0.00402	0.15	0.17
log(Zip Deposits)	11.61	3.50	3.106	9.37	14.27	11.64	2.94	2.64	9.67	13.97
CRA 3yr growth	0.05	0.07		-0.01	0.12	-0.11	0.04		-0.15	-0.06
Deposit 3yr growth	0.05	0.03		0.00	0.08	0.10	0.08		0.01	0.20
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	0.18		0.07	0.51	0.30	0.17		0.07	0.49
Mortgage 3yr growth	0.03	0.07		-0.04	0.11	0.02	0.09		-0.07	0.15
Payroll 3yr growth	0.04	0.02		0.01	0.07	0.00	0.02		-0.02	0.02

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. 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)
DF per dollar	-0.5067***	-0.7017***	-0.6339***	-0.9833***	-0.4451***	-0.4498***
	(0.0611)	(0.0782)	(0.0949)	(0.1089)	(0.0520)	(0.0585)
log(Deposits)	-0.0205***	-0.0206***	-0.0233***	-0.0233***	-0.0183***	-0.0183***
	(0.0006)	(0.0006)	(0.0010)	(0.0010)	(0.0005)	(0.0005)
Acq. branch/presence	0.0531***	0.0504***	0.0568***	0.0521***	0.0477***	0.0448***
	(0.0066)	(0.0067)	(0.0109)	(0.0113)	(0.0044)	(0.0045)
Branch owned 3plus years	-0.0055***	-0.0059***	-0.0054*	-0.0061*	-0.0062***	-0.0067***
	(0.0015)	(0.0015)	(0.0031)	(0.0033)	(0.0011)	(0.0012)
Deposit 3yr growth	0.0006		0.0023		$-2.62e$-5	
	(0.0011)		(0.0018)		(0.0012)	
Mortgage 3yr growth	-0.0071**		-0.0077		-0.0054*	
	(0.0029)		(0.0050)		(0.0029)	
CRA 3yr growth	-0.0018**		-0.0013		-0.0017*	
	(0.0008)		(0.0019)		(0.0009)	
Establishments 3yr growth	-0.1440***		-0.2644***		-0.0376**	
	(0.0260)		(0.0423)		(0.0188)	
Payroll 3yr growth	0.0002		-0.0072		0.0067	
	(0.0060)		(0.0110)		(0.0068)	
Low to Moderate Income Area	-0.0049***		-0.0109***		0.0007	
	(0.0016)		(0.0026)		(0.0012)	
State × Year FE	✓		✓		✓	
Bank × Year FE	✓	✓	✓	✓	✓	✓
County × Year FE		✓		✓		✓
Observations	1,594,989	1,594,989	690,261	690,261	904,728	904,728
R^2	0.09939	0.13228	0.05002	0.11053	0.15713	0.21608

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. 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)
DF per dollar	-0.1047***	-0.1201***	-0.3318***	-0.2969***	-0.0749***	-0.1031***
	(0.0106)	(0.0070)	(0.0689)	(0.0541)	(0.0041)	(0.0043)
log(Zip deposits)	0.0003***	0.0003***	0.0005***	0.0005***	0.0003***	0.0003***
	(1.74*e*-5)	(1.63*e*-5)	(9.91*e*-5)	(0.0001)	(8.65*e*-6)	(9*e*-6)
Deposit 3yr growth	-0.0005***		0.0010		-0.0007***	
	(0.0001)		(0.0007)		(0.0001)	
Mortgage 3yr growth	1.24*e*-5		-0.0042*		0.0006*	
	(0.0004)		(0.0022)		(0.0003)	
CRA 3yr growth	-0.0004**		0.0002		-0.0006***	
	(0.0002)		(0.0006)		(0.0002)	
Establishments 3yr growth	0.0265***		0.0794***		0.0170***	
	(0.0034)		(0.0132)		(0.0018)	
Payroll 3yr growth	0.0011		0.0007		0.0011	
	(0.0007)		(0.0027)		(0.0007)	
Low to Moderate Income Area	-0.0006***		0.0005		-0.0008***	
	(0.0001)		(0.0006)		(9.11*e*-5)	
State × Year FE	✓		✓		✓	
Bank × Year FE	✓	✓	✓	✓	✓	✓
County × Year FE		✓		✓		✓
Observations	13,853,404	13,854,647	1,465,309	1,465,449	12,388,095	12,389,198
R^2	0.02859	0.03848	0.01965	0.03854	0.03231	0.04680
Within R^2	0.00100	0.00078	0.00274	0.00144	0.00079	0.00072

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)
Sophisticated zipcode			0.0034***	0.0038***
			(0.0006)	(0.0006)
College frac	0.0087***	0.0167***		
	(0.0027)	(0.0030)		
Stock market frac	0.0215***	0.0153***		
	(0.0041)	(0.0041)		
log(Income)	-0.0043***	-0.0061***	-0.0016***	-0.0025***
	(0.0007)	(0.0008)	(0.0005)	(0.0006)
Age Q1-Q2	0.0012**	0.0012**	0.0011*	0.0012**
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Age Q2-Q3	0.0004	0.0006	0.0010	0.0013*
	(0.0007)	(0.0007)	(0.0008)	(0.0008)
Age >Q3	0.0002	0.0009	0.0019*	0.0028***
	(0.0009)	(0.0009)	(0.0010)	(0.0011)
County deposit HHI	-0.0034		-0.0033	
	(0.0021)		(0.0022)	
Population density	0.0046**		0.0072***	
	(0.0021)		(0.0023)	
Controls	✓	✓	✓	✓
State × Year FE	✓		✓	
Bank × Year FE	✓	✓	✓	✓
County × Year FE		✓		✓
Observations	1,594,989	1,594,989	1,594,989	1,594,989
R^2	0.09946	0.13229	0.09927	0.13211
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)
Sophisticated zipcode					0.0059***	0.0062***	0.0009*	0.0017***
					(0.0008)	(0.0007)	(0.0005)	(0.0006)
College frac	0.0107**	0.0185***	0.0108***	0.0171***				
	(0.0045)	(0.0048)	(0.0026)	(0.0032)				
Stock market frac	0.0351***	0.0304***	0.0009	-0.0031				
	(0.0049)	(0.0053)	(0.0038)	(0.0044)				
log(Income)	-0.0076***	-0.0092***	-0.0021***	-0.0039***	-0.0029***	-0.0035***	-0.0005	-0.0018***
	(0.0010)	(0.0013)	(0.0005)	(0.0006)	(0.0009)	(0.0010)	(0.0005)	(0.0005)
Age Q1-Q2	0.0029***	0.0026***	-0.0006	-0.0006	0.0027***	0.0026***	-0.0008	-0.0008
	(0.0006)	(0.0006)	(0.0005)	(0.0006)	(0.0007)	(0.0006)	(0.0005)	(0.0006)
Age Q2-Q3	0.0022**	0.0022**	-0.0014**	-0.0015**	0.0031***	0.0036***	-0.0015**	-0.0016**
	(0.0009)	(0.0008)	(0.0006)	(0.0007)	(0.0010)	(0.0009)	(0.0006)	(0.0007)
Age >Q3	0.0028**	0.0031**	-0.0020***	-0.0015*	0.0060***	0.0069***	-0.0019***	-0.0013
	(0.0013)	(0.0013)	(0.0008)	(0.0009)	(0.0012)	(0.0012)	(0.0007)	(0.0008)
County deposit HHI	0.0019		-0.0066***		0.0039		-0.0071***	
	(0.0037)		(0.0019)		(0.0039)		(0.0019)	
Population density	0.0038		0.0091***		0.0066**		0.0115***	
	(0.0030)		(0.0018)		(0.0033)		(0.0018)	
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 income, 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)
Sophisticated zipcode			0.0015***	0.0014***
			(7.46e-5)	(8.08e-5)
College frac	0.0043***	0.0045***		
	(0.0003)	(0.0003)		
Stock market frac	0.0009***	0.0008***		
	(0.0004)	(0.0003)		
log(Income)	-0.0003***	-0.0003***	8.45e-5	7.88e-5*
	(5.33e-5)	(3.91e-5)	(5.88e-5)	(4.52e-5)
Age Q1-Q2	-0.0005***	-0.0004***	-0.0006***	-0.0005***
	(7.34e-5)	(6.68e-5)	(7.63e-5)	(7.05e-5)
Age Q2-Q3	-0.0010***	-0.0009***	-0.0011***	-0.0009***
	(9.64e-5)	(8.81e-5)	(9.53e-5)	(8.93e-5)
Age >Q3	-0.0013***	-0.0013***	-0.0013***	-0.0012***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
County deposit HHI	-0.0024***		-0.0021***	
	(0.0002)		(0.0002)	
Population density	-0.0004		0.0002	
	(0.0004)		(0.0004)	
Controls	✓	✓	✓	✓
Bank × Year FE	✓	✓	✓	✓
State × Year FE	✓		✓	
County × Year FE		✓		✓
Observations	13,853,404	13,853,404	13,853,404	13,853,404
R^2	0.02871	0.03854	0.02867	0.03850

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)
Sophisticated zipcode					0.0032***	0.0034***	0.0013***	0.0012***
					(0.0005)	(0.0006)	(5e-5)	(4.82e-5)
College frac	0.0128***	0.0141***	0.0037***	0.0036***				
	(0.0019)	(0.0019)	(0.0002)	(0.0002)				
Stock market frac	0.0009	0.0006	0.0008***	0.0009***				
	(0.0024)	(0.0022)	(0.0002)	(0.0002)				
log(Income)	-0.0003	-0.0005**	-0.0004***	-0.0003***	0.0008**	0.0008**	$-5.62e$-5**	$-1.45e$-6
	(0.0003)	(0.0002)	(2.88e-5)	(3.18e-5)	(0.0003)	(0.0003)	(2.4e-5)	(2.73e-5)
Age Q1-Q2	-0.0018***	-0.0015***	-0.0003***	-0.0002***	-0.0021***	-0.0017***	-0.0004***	-0.0004***
	(0.0005)	(0.0005)	(3.86e-5)	(3.86e-5)	(0.0005)	(0.0005)	(4.09e-5)	(4.02e-5)
Age Q2-Q3	-0.0025***	-0.0023***	-0.0008***	-0.0007***	-0.0027***	-0.0024***	-0.0009***	-0.0008***
	(0.0006)	(0.0006)	(5.31e-5)	(5.43e-5)	(0.0006)	(0.0006)	(5.69e-5)	(5.78e-5)
Age >Q3	-0.0034***	-0.0036***	-0.0010***	-0.0010***	-0.0034***	-0.0033***	-0.0010***	-0.0010***
	(0.0007)	(0.0008)	(6.6e-5)	(6.72e-5)	(0.0006)	(0.0008)	(7.03e-5)	(7e-5)
County deposit HHI	-0.0013*		-0.0024***		-0.0006		-0.0020***	
	(0.0007)		(0.0002)		(0.0006)		(0.0002)	
Population density	0.0039**		-0.0014***		0.0061***		-0.0009***	
	(0.0015)		(0.0001)		(0.0016)		(0.0001)	
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Bank × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
State × Year FE	✓		✓		✓		✓	
County × Year FE		✓		✓		✓		✓
Observations	1,465,309	1,465,309	12,388,095	12,388,095	1,465,309	1,465,309	12,388,095	12,388,095
R^2	0.02032	0.03886	0.03242	0.04684	0.02005	0.03861	0.03240	0.04681

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. The analysis is conducted separately by interest rate regime. 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)
DF per dollar	-0.7019***	-0.5859***	-0.7235***	-0.7545***	-0.4144**	-0.8916***	-1.222***	-1.865***
	(0.1051)	(0.1109)	(0.1202)	(0.1380)	(0.1690)	(0.1704)	(0.1752)	(0.2147)
log(Deposits)	-0.0192***	-0.0196***	-0.0175***	-0.0177***	-0.0246***	-0.0243***	-0.0338***	-0.0335***
	(0.0023)	(0.0023)	(0.0029)	(0.0030)	(0.0021)	(0.0021)	(0.0037)	(0.0036)
Acq. branch/presence	0.0681***	0.0627***	0.0392**	0.0361**	0.0177**	0.0181**	0.1022***	0.0959***
	(0.0216)	(0.0233)	(0.0159)	(0.0162)	(0.0077)	(0.0078)	(0.0233)	(0.0253)
Branch owned 3plus years	0.0010	0.0002	-0.0114**	-0.0112**	-0.0174**	-0.0174***	0.0124	0.0114
	(0.0033)	(0.0040)	(0.0045)	(0.0045)	(0.0067)	(0.0062)	(0.0087)	(0.0090)
Deposit 3yr growth	0.0037*		0.0195*		-0.0043		-0.0347	
	(0.0019)		(0.0108)		(0.0117)		(0.0210)	
Mortgage 3yr growth	-0.0073		-0.0025		-0.0100		-0.0093	
	(0.0058)		(0.0116)		(0.0089)		(0.0080)	
CRA 3yr growth	-0.0015		-0.0060		0.0042		-0.0010	
	(0.0015)		(0.0084)		(0.0088)		(0.0116)	
Establishments 3yr growth	-0.0232		-0.1102**		-0.4281***		-0.5546***	
	(0.0833)		(0.0484)		(0.1198)		(0.1026)	
Payroll 3yr growth	-0.0105		-0.0537***		-0.0099		0.0186	
	(0.0129)		(0.0150)		(0.0273)		(0.0219)	
Low to Moderate Income Area	-0.0015		-0.0075**		-0.0114***		-0.0208***	
	(0.0029)		(0.0035)		(0.0038)		(0.0058)	
State × Year FE	✓		✓		✓		✓	
Bank × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
County × Year FE		✓		✓		✓		✓
Observations	142,608	142,608	132,325	132,325	292,360	292,360	122,968	122,968
R^2	0.04588	0.10311	0.03728	0.08776	0.04335	0.10795	0.05430	0.11431

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)
DF per dollar	-0.4392***	-0.5324***	-0.6513***	-0.5398***	-0.3630***	-0.4356***	-0.4847***	-0.3550***
	(0.1056)	(0.1264)	(0.1040)	(0.1330)	(0.0845)	(0.0924)	(0.0854)	(0.1125)
log(Deposits)	-0.0165***	-0.0164***	-0.0174***	-0.0176***	-0.0188***	-0.0188***	-0.0204***	-0.0204***
	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0008)	(0.0007)	(0.0010)	(0.0010)
Acq. branch/presence	0.0395***	0.0363***	0.0544***	0.0501***	0.0533***	0.0511***	0.0435***	0.0418***
	(0.0050)	(0.0055)	(0.0091)	(0.0093)	(0.0090)	(0.0089)	(0.0111)	(0.0113)
Branch owned 3plus years	-0.0010	-0.0004	-0.0058**	-0.0076***	-0.0080***	-0.0079***	-0.0095***	-0.0108***
	(0.0019)	(0.0024)	(0.0026)	(0.0026)	(0.0020)	(0.0020)	(0.0026)	(0.0029)
Deposit 3yr growth	3.23e-5		0.0060		0.0068		-0.0152	
	(0.0012)		(0.0131)		(0.0094)		(0.0115)	
Mortgage 3yr growth	-0.0027		-0.0139		-0.0087		-0.0032	
	(0.0041)		(0.0089)		(0.0064)		(0.0054)	
CRA 3yr growth	-0.0012		-0.0086		0.0010		-0.0071*	
	(0.0010)		(0.0053)		(0.0027)		(0.0037)	
Establishments 3yr growth	-0.0323		-0.0236		-0.0377		-0.0360	
	(0.0283)		(0.0313)		(0.0333)		(0.0460)	
Payroll 3yr growth	-0.0018		0.0179		0.0044		0.0095	
	(0.0142)		(0.0143)		(0.0110)		(0.0185)	
Low to Moderate Income Area	0.0041*		0.0049*		-0.0006		-0.0048*	
	(0.0023)		(0.0028)		(0.0021)		(0.0028)	
State × Year FE	✓		✓		✓		✓	
Bank × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
County × Year FE		✓		✓		✓		✓
Observations	222,109	222,109	163,603	163,603	355,275	355,275	163,741	163,741
R^2	0.16764	0.24295	0.17334	0.22664	0.15645	0.21175	0.13534	0.19068

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

Table 11: Openings by Regime

@@@update This table reports year-by-year estimates of Equation (5a), analyzing the relationship between the deposit franchise value (DF per dollar) and branch closures. Panels A and B focus on large banks, while Panels C and D focus on small banks. Panels A and C include state × year fixed effects, and Panels B and D incorporate county × year fixed effects. The dependent variable in all panels is an indicator for branch closure (Closed = 1). The coefficients of the control variables are suppressed. Standard errors (reported in parentheses) are clustered at the bank level. We use *,**, and *** to 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)
DF per dollar	-0.8328***	-0.7263***	-0.6685***	-0.5194***	-0.1800***	-0.1733***	-0.2621**	-0.1997*
	(0.1247)	(0.1247)	(0.1073)	(0.0991)	(0.0363)	(0.0448)	(0.1284)	(0.1043)
log(Zip deposits)	0.0010***	0.0011***	0.0011***	0.0011***	0.0002***	0.0002***	0.0004**	0.0004**
	(8.42e-5)	(0.0001)	(0.0002)	(0.0002)	(5.74e-5)	(5.88e-5)	(0.0002)	(0.0002)
Deposit 3yr growth	0.0011		0.0099*		0.0035*		0.0069***	
	(0.0008)		(0.0056)		(0.0019)		(0.0016)	
Mortgage 3yr growth	-0.0038		-0.0223**		0.0019		-0.0031	
	(0.0028)		(0.0088)		(0.0025)		(0.0020)	
CRA 3yr growth	1.88e-5		0.0094**		0.0005		-0.0003	
	(0.0010)		(0.0044)		(0.0010)		(0.0008)	
Establishments 3yr growth	0.1828***		0.0759***		0.0182*		0.0355*	
	(0.0270)		(0.0217)		(0.0103)		(0.0178)	
Payroll 3yr growth	-0.0101		0.0018		0.0006		0.0082**	
	(0.0060)		(0.0092)		(0.0028)		(0.0036)	
Low to Moderate Income Area	-0.0013		-0.0030*		0.0011**		0.0011*	
	(0.0016)		(0.0018)		(0.0005)		(0.0006)	
State × Year FE	✓		✓		✓		✓	
Bank × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
County × Year FE		✓		✓		✓		✓
Observations	287,681	287,704	237,747	237,764	628,108	628,206	311,773	311,775
R^2	0.01972	0.04350	0.02712	0.04356	0.00909	0.02018	0.01371	0.03093

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)
DF per dollar	-0.1728***	-0.1962***	-0.0814***	-0.1056***	-0.0600***	-0.0845***	-0.0304***	-0.0434***
	(0.0127)	(0.0112)	(0.0071)	(0.0082)	(0.0039)	(0.0050)	(0.0033)	(0.0041)
log(Zip deposits)	0.0005***	0.0005***	0.0003***	0.0003***	0.0002***	0.0002***	0.0002***	0.0002***
	(1.91e-5)	(1.93e-5)	(2.13e-5)	(2.26e-5)	(5.76e-6)	(6.08e-6)	(7.35e-6)	(8.07e-6)
Deposit 3yr growth	-0.0004***		-0.0012		-0.0014***		−1.94e-5	
	(0.0001)		(0.0009)		(0.0004)		(0.0006)	
Mortgage 3yr growth	0.0018***		-0.0016*		0.0002		0.0002	
	(0.0005)		(0.0009)		(0.0004)		(0.0004)	
CRA 3yr growth	-0.0001		-0.0046***		-0.0002		−1.59e-5	
	(0.0002)		(0.0010)		(0.0003)		(0.0003)	
Establishments 3yr growth	0.0289***		0.0255***		0.0097***		0.0059*	
	(0.0039)		(0.0036)		(0.0023)		(0.0031)	
Payroll 3yr growth	0.0027*		-0.0012		0.0007		-0.0010	
	(0.0015)		(0.0014)		(0.0009)		(0.0013)	
Low to Moderate Income Area	-0.0012***		-0.0011***		-0.0005***		-0.0005***	
	(0.0002)		(0.0003)		(9.78e-5)		(0.0001)	
State × Year FE	✓		✓		✓		✓	
Bank × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
County × Year FE		✓		✓		✓		✓
Observations	3,596,830	3,597,113	2,274,949	2,275,013	4,535,736	4,536,479	1,980,580	1,980,593
R^2	0.03720	0.05225	0.03097	0.04600	0.02384	0.03671	0.02158	0.03461

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)
DF per dollar	-0.8155***	-0.7474***	-0.6281***	-0.4617***
	(0.1357)	(0.1480)	(0.1218)	(0.1291)
Drop in visits			0.0096***	0.0078**
			(0.0028)	(0.0036)
log(Distance km)			0.0069***	0.0107***
			(0.0019)	(0.0022)
Controls	✓	✓	✓	✓
State × Year FE	✓		✓	
Bank × Year FE	✓	✓	✓	✓
County × Year FE		✓		✓
Observations	131,464	131,464	131,259	131,259
R^2	0.06181	0.09154	0.06243	0.09229

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)
DF per dollar	-1.173***	-1.221***	-0.8942***	-0.6324***	-0.3642**	-0.3642**	-0.3925***	-0.2620
	(0.2118)	(0.1867)	(0.1955)	(0.1896)	(0.1653)	(0.1653)	(0.1179)	(0.1660)
Drop in visits			0.0130	0.0132			0.0082***	0.0054***
			(0.0080)	(0.0097)			(0.0015)	(0.0020)
log(Distance km)			0.0137***	0.0196***			0.0012	0.0040**
			(0.0032)	(0.0037)			(0.0013)	(0.0017)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
State × Year FE	✓		✓				✓	
Bank × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
County × Year FE		✓		✓	✓	✓		✓
Observations	58,459	58,459	58,432	58,432	73,005	73,005	72,827	72,827
R^2	0.03230	0.09018	0.03351	0.09170	0.16553	0.16553	0.11069	0.16602

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)
DF per dollar	-0.0369**	-0.0380***	-0.0283**	-0.0366***
	(0.0157)	(0.0096)	(0.0136)	(0.0099)
Drop in visits			0.0008***	0.0009***
			(0.0003)	(0.0002)
log(Distance km)			$-1.05e$-5	-0.0001
			(0.0001)	(0.0001)
Controls	✓	✓	✓	✓
Bank × Year FE	✓	✓	✓	✓
State × Year FE	✓		✓	
County × Year FE		✓		✓
Observations	916,258	916,258	914,266	914,266
R^2	0.02559	0.03983	0.02574	0.03997

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)
DF per dollar	-0.2030**	-0.1424*	-0.1787**	-0.1353*	-0.0102**	-0.0270***	-0.0038	-0.0258***
	(0.0953)	(0.0740)	(0.0781)	(0.0745)	(0.0051)	(0.0062)	(0.0051)	(0.0063)
Drop in visits			0.0020	0.0017			0.0006***	0.0007***
			(0.0015)	(0.0015)			(0.0001)	(0.0001)
log(Distance km)			0.0001	1.98e-5			5.81e-5	-0.0001
			(0.0005)	(0.0007)			(7.34e-5)	(8.61e-5)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Bank × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
State × Year FE	✓		✓		✓		✓	
County × Year FE		✓		✓		✓		✓
Observations	118,129	118,129	117,699	117,699	798,129	798,129	796,567	796,567
R^2	0.01580	0.04064	0.01600	0.04083	0.03187	0.05116	0.03203	0.05131

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

Internet Appendix: The Decline of Branch Banking

Rajesh P. Narayanan; Dimuthu Ratnadiwakara; Philip E. Strahan

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)
DF per dollar	-0.4776***	-0.6729***	-0.6051***	-0.9543***	-0.4132***	-0.4203***
	(0.0597)	(0.0774)	(0.0920)	(0.1079)	(0.0527)	(0.0594)
Openings by other banks	0.0028***	0.0024***	0.0032***	0.0027***	0.0027***	0.0023***
	(0.0004)	(0.0004)	(0.0006)	(0.0007)	(0.0006)	(0.0006)
log(Deposits)	-0.0205***	-0.0207***	-0.0234***	-0.0234***	-0.0183***	-0.0183***
	(0.0006)	(0.0006)	(0.0010)	(0.0010)	(0.0005)	(0.0005)
Acq. branch/presence	0.0529***	0.0503***	0.0566***	0.0520***	0.0476***	0.0448***
	(0.0066)	(0.0067)	(0.0109)	(0.0113)	(0.0045)	(0.0045)
Branch owned 3plus years	-0.0055***	-0.0059***	-0.0054*	-0.0062*	-0.0062***	-0.0067***
	(0.0015)	(0.0015)	(0.0031)	(0.0033)	(0.0011)	(0.0012)
Deposit 3yr growth	0.0005		0.0021		-8.98×10^{-5}	
	(0.0011)		(0.0018)		(0.0012)	
Mortgage 3yr growth	-0.0071**		-0.0076		-0.0054*	
	(0.0029)		(0.0050)		(0.0029)	
CRA 3yr growth	-0.0018**		-0.0013		-0.0016*	
	(0.0008)		(0.0019)		(0.0009)	
Establishments 3yr growth	-0.1502***		-0.2723***		-0.0431**	
	(0.0263)		(0.0425)		(0.0189)	
Payroll 3yr growth	-5.98×10^{-5}		-0.0075		0.0064	
	(0.0060)		(0.0111)		(0.0068)	
Low to Moderate Income Area	-0.0048***		-0.0107***		0.0008	
	(0.0016)		(0.0026)		(0.0012)	
State × Year FE	✓		✓		✓	
Bank × Year FE	✓	✓	✓	✓	✓	✓
County × Year FE		✓		✓		✓
Observations	1,595,173	1,595,173	690,261	690,261	904,912	904,912
R^2	0.09942	0.13230	0.05006	0.11055	0.15715	0.21611

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

Table IA.2: Baseline Closure Model - Version 3

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)
DF per dollar	-0.6138***	-0.7793***	-0.6752***	-0.9936***	-0.5620***	-0.5314***
	(0.0612)	(0.0828)	(0.0919)	(0.1100)	(0.0653)	(0.0696)
log(Bank-County Mortgage Volume)	-0.0005	-0.0007	-0.0010	-0.0006	-0.0003	-0.0008***
	(0.0004)	(0.0004)	(0.0008)	(0.0015)	(0.0003)	(0.0003)
log(Bank-County CRA Volume)	4.47×10^{-5}	-0.0002	0.0005	0.0009	-6.61×10^{-5}	-0.0004
	(0.0003)	(0.0004)	(0.0006)	(0.0008)	(0.0003)	(0.0003)
log(Deposits)	-0.0220***	-0.0220***	-0.0233***	-0.0234***	-0.0206***	-0.0204***
	(0.0006)	(0.0007)	(0.0010)	(0.0010)	(0.0006)	(0.0006)
Acq. branch/presence	0.0534***	0.0510***	0.0560***	0.0508***	0.0484***	0.0461***
	(0.0067)	(0.0070)	(0.0108)	(0.0114)	(0.0048)	(0.0049)
Branch owned 3plus years	-0.0055***	-0.0053***	-0.0055*	-0.0067**	-0.0065***	-0.0060***
	(0.0016)	(0.0015)	(0.0030)	(0.0029)	(0.0013)	(0.0014)
Deposit 3yr growth	0.0005		0.0027		-0.0014	
	(0.0013)		(0.0018)		(0.0017)	
Mortgage 3yr growth	-0.0075**		-0.0074		-0.0067*	
	(0.0033)		(0.0050)		(0.0036)	
CRA 3yr growth	-0.0014		-0.0014		-0.0010	
	(0.0010)		(0.0019)		(0.0011)	
Establishments 3yr growth	-0.1487***		-0.2493***		-0.0273	
	(0.0289)		(0.0450)		(0.0235)	
Payroll 3yr growth	-0.0013		-0.0087		0.0087	
	(0.0068)		(0.0103)		(0.0089)	
Low to Moderate Income Area	-0.0053***		-0.0107***		0.0015	
	(0.0017)		(0.0024)		(0.0015)	
State × Year FE	✓		✓		✓	
Bank × Year FE	✓	✓	✓	✓	✓	✓
County × Year FE		✓		✓		✓
Observations	1,283,610	1,283,610	687,467	687,467	596,143	596,143
R^2	0.07471	0.11328	0.05001	0.11055	0.11430	0.18919

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

Table IA.3: 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)
DF per dollar	-0.0956***	-0.1122***	-0.3149***	-0.2835***	-0.0667***	-0.0959***
	(0.0102)	(0.0067)	(0.0654)	(0.0517)	(0.0040)	(0.0041)
Closures by other banks	0.0013***	0.0013***	0.0028***	0.0026***	0.0012***	0.0011***
	(9.06×10^{-5})	(8.35×10^{-5})	(0.0007)	(0.0007)	(5.9×10^{-5})	(5.75×10^{-5})
log(Zip deposits)	0.0003***	0.0003***	0.0005***	0.0005***	0.0002***	0.0003***
	(1.58×10^{-5})	(1.49×10^{-5})	(8.67×10^{-5})	(8.85×10^{-5})	(7.88×10^{-6})	(8.25×10^{-6})
Deposit 3yr growth	-0.0005***		0.0010		-0.0007***	
	(0.0001)		(0.0007)		(0.0001)	
Mortgage 3yr growth	7.53×10^{-5}		-0.0041*		0.0006**	
	(0.0004)		(0.0021)		(0.0003)	
CRA 3yr growth	-0.0004***		0.0002		-0.0006***	
	(0.0002)		(0.0006)		(0.0002)	
Establishments 3yr growth	0.0260***		0.0785***		0.0165***	
	(0.0034)		(0.0131)		(0.0018)	
Payroll 3yr growth	0.0014**		0.0012		0.0014**	
	(0.0007)		(0.0027)		(0.0007)	
Low to Moderate Income Area	-0.0005***		0.0006		-0.0007***	
	(0.0001)		(0.0006)		(9.1×10^{-5})	
State × Year FE	✓		✓		✓	
Bank × Year FE	✓	✓	✓	✓	✓	✓
County × Year FE		✓		✓		✓
Observations	13,853,404	13,854,647	1,465,309	1,465,449	12,388,095	12,389,198
R^2	0.02870	0.03858	0.01987	0.03872	0.03241	0.04689

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

Table IA.4: Baseline Opening Model - Version 3

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)
DF per dollar	-0.0927***	-0.1201***	-0.2435***	-0.2969***	-0.0750***	-0.1031***
	(0.0073)	(0.0070)	(0.0517)	(0.0541)	(0.0038)	(0.0043)
log(County Mortgage Volume)	-0.0002		0.0015***		-0.0009***	
	(0.0002)		(0.0005)		(8.03×10^{-5})	
log(County CRA Volume)	0.0003**		-0.0007**		0.0008***	
	(0.0001)		(0.0003)		(6.8×10^{-5})	
log(Zip deposits)	0.0003***	0.0003***	0.0005***	0.0005***	0.0003***	0.0003***
	(1.65×10^{-5})	(1.63×10^{-5})	(9.55×10^{-5})	(0.0001)	(8.62×10^{-6})	(9×10^{-6})
Deposit 3yr growth	-0.0005***		0.0006		-0.0006***	
	(0.0001)		(0.0007)		(0.0001)	
Mortgage 3yr growth	0.0003		-0.0053**		0.0013***	
	(0.0005)		(0.0024)		(0.0003)	
CRA 3yr growth	-0.0004*		0.0011		-0.0008***	
	(0.0002)		(0.0008)		(0.0002)	
Establishments 3yr growth	0.0275***		0.0476***		0.0231***	
	(0.0022)		(0.0080)		(0.0018)	
Payroll 3yr growth	0.0015**		0.0034		0.0012*	
	(0.0007)		(0.0028)		(0.0007)	
Low to Moderate Income Area	-0.0008***		9.54×10^{-5}		-0.0010***	
	(0.0001)		(0.0006)		(9.61×10^{-5})	
State × Year FE	✓		✓		✓	
Bank × Year FE	✓	✓	✓	✓	✓	✓
County × Year FE		✓		✓		✓
Observations	13,853,404	13,854,647	1,465,309	1,465,449	12,388,095	12,389,198
R^2	0.02860	0.03848	0.01987	0.03854	0.03234	0.04680

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

Table IA.5: 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 (< 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)
DF per dollar	-0.1048***	-0.1206***	-0.3335***	-0.2981***	-0.0749***	-0.1035***
	(0.0108)	(0.0071)	(0.0701)	(0.0562)	(0.0041)	(0.0044)
log(Zip deposits)	0.0003***	0.0003***	0.0005***	0.0006***	0.0003***	0.0003***
	(1.8×10^{-5})	(1.69×10^{-5})	(0.0001)	(0.0001)	(8.8×10^{-6})	(9.14×10^{-6})
Deposit 3yr growth	-0.0005***		0.0006		-0.0006***	
	(0.0001)		(0.0007)		(0.0001)	
Mortgage 3yr growth	6.85×10^{-5}		-0.0041*		0.0006**	
	(0.0004)		(0.0023)		(0.0003)	
CRA 3yr growth	-0.0004**		2.1×10^{-5}		-0.0005***	
	(0.0002)		(0.0007)		(0.0002)	
Establishments 3yr growth	0.0266***		0.0825***		0.0168***	
	(0.0036)		(0.0141)		(0.0019)	
Payroll 3yr growth	0.0015**		0.0009		0.0016**	
	(0.0007)		(0.0026)		(0.0007)	
Low to Moderate Income Area	-0.0006***		0.0005		-0.0008***	
	(0.0001)		(0.0006)		(9.41×10^{-5})	
State × Year FE	✓		✓		✓	
Bank × Year FE	✓	✓	✓	✓	✓	✓
County × Year FE		✓		✓		✓
Observations	11,805,862	11,806,930	1,248,173	1,248,296	10,557,689	10,558,634
R^2	0.03157	0.04285	0.01986	0.04083	0.03617	0.05288

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