Bank Branch Density and Fragility

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ABSTRACT

Bank branch density, defined as the number of a bank's branches divided by its total deposits, declined significantly between 2010 and 2022. We show that the transition from branch-based to digital banking has concentrated financially and technologically sophisticated depositors in low-density banks, thereby increasing the flightiness of their deposits. Survey microdata on consumers' bank choices show that depositors at low-density banks are more likely to read financial news, invest in money market mutual funds, and report intentions to switch banks. This pattern suggests that low-density banks attract a financially sophisticated clientele, not that banks' digital platforms make depositors more attentive. This clientele exposes low-density banks to deposit flightiness risk. When interest rates rose in 2023, these banks suffered steeper stock declines and larger deposit outflows, even conditional on asset-side losses, than typical banks.

JEL : E44, E52, G20, G21, G28.
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The regional bank failures of March and May 2023 represent the most significant systemic disruption in the U.S. banking sector since the Global Financial Crisis. The three largest banks to fail—Silicon Valley Bank (SVB), Signature Bank, and First Republic Bank—shared a striking structural feature: the absence of a traditional branch network. SVB operated roughly one branch for every $10 billion in deposits; the median U.S. bank operates over 100. Their turmoil raises the question: How does the broad shift away from branch-based banking affect financial stability?

We show that the shift away from branches concentrates financially and technologically sophisticated depositors in a limited set of low-density banks which makes their deposits more flighty. Survey microdata on consumers' bank choices show that depositors at low-density banks are more likely to read financial news, invest in money market mutual funds, and report intentions to switch banks. Crucially, their technological sophistication extends beyond banking; these depositors are more likely to use online real estate platforms and drive electric vehicles, behaviors that cannot plausibly be caused by a bank's mobile app. This pattern suggests that low-density banks attract a clientele that is already sophisticated, not that such banks make depositors more attentive. This clientele exposes low-density banks to deposit flightiness risk. When interest rates rose in 2023, these banks suffered steeper stock declines and larger deposit outflows, even conditional on asset-side losses, than typical banks.

Branch density is a measure defined by the number of branches a bank operates per $1 billion of deposits. Compared to the rest of the banking sector, the banks that failed had strikingly low branch density. The median branch density of all FDIC-insured bank holding companies as of June 30, 2022, was 14.9—that is, the median bank operated 14.9 branches for every $1 billion in deposits. In sharp contrast, the three banks that failed in March and May 2023 operated with extremely low branch density. The branch densities of SVB, Signature Bank, and First Republic Bank were 0.10, 0.36, and 0.53, respectively, well below the 10th percentile of the branch density distribution, which was around 5 in 2022. But low branch density is a characteristic of banks other than the three that failed. As digitization has reduced branch density across the banking system, it has created a subset of low-density banks with business models that attract a particular type of customer.

We show that compared to typical banks, low-density banks serve a financially sophisticated clientele. We combine data from the ACS with survey microdata from MRI-Simmons to show that depositors at low-density banks are wealthier, younger, and more highly educated. Low-density banks serve counties with more affluent, younger, and more highly educated households. But even within three-digit zip codes, consumers who use low-density banks have 10% higher household income, are 19% less likely to be age 60 or greater, and are 7% more likely to have a college degree. Yet their sophistication goes beyond demographics. Depositors at low-density banks are 19% more likely to rank the deposit rate as an important factor when choosing banks, 14% more likely to invest in money market funds, and 30% more likely to report intentions to switch banks in the next 12 months. The results on money market funds echo past findings by Xiao (2020) that they are an important alternative to deposits. Even within banks, depositors who value branch networks are less sensitive to deposit rates—suggesting that the correlation between financial and technological sophistication reflects consumer preferences, not bank-level confounds.

Depositors at low-density banks are also more technologically sophisticated, even in nonfinancial contexts. Besides being more likely to use mobile banking and fast-payment apps such as Zelle, they are more likely to use online real estate platforms, purchase insurance online rather than through agents, and drive electric vehicles. These nonfinancial behaviors cannot plausibly be caused by the quality of a bank's mobile app. The pattern suggests that low-density banks attract a clientele that is technologically sophisticated across many domains—not simply that digital banking platforms change how depositors behave.

Low-density banks attract this sophisticated clientele with high deposit rates and large investments in technology. Because financial and technological sophistication are correlated among consumers, banks with few branches must compete along both dimensions simultaneously—they cannot attract tech-savvy depositors without also attracting rate-sensitive ones. In the period preceding the crisis, RateWatch data show that banks with low branch density offered higher deposit rates; SWZD Aberdeen data show that they spent more on IT; and Lightcast job posting data show that they tilted their hiring toward employees with technical skills rather than customer service experience. These investments appear to increase the use of online banking: Semrush data show that low-density banks have a higher ratio of website visits to total deposits.

These facts about depositors at low-density banks predict that these banks face greater risks of desposit flightiness, especially when interest rates rise. The theoretical literature highlights that interest rate hikes can trigger depositor runs if the franchise value of the bank deteriorates (Haddad, Hartman-Glaser, and Muir (2023), Jiang et al. (2024), Drechsler et al. (2026). Low-density banks are uniquely vulnerable to depositor runs for two reasons: insured depositors may be more likely to leave when deposit spreads rise, and uninsured depositors are more likely to leave because they are more attentive to financial news and their bank's solvency.

The crisis of 2023 provides a test of whether this concentration of sophisticated depositors at low-density banks translates into fragility. We conduct two event studies to study the relationship between branch density and banks' stock returns: one centered on the March failures of SVB and Signature Bank, and another around the end-of-April failure of First Republic Bank. Low-density banks suffered substantially worse stock returns during both episodes. For instance, around the collapse of SVB, a one standard deviation decrease in branch density is associated with 2.8 percentage points lower returns, corresponding to approximately 20% of the sample's mean returns. The effect is nonlinear and most pronounced among banks with exceptionally low branch density. Specifically, banks with density lower than 2.5, approximately the 5th percentile of the full bank distribution and the 10th percentile among publicly traded banks, experienced 11 percentage point lower returns than those banks with density above 10, a level close to the sample mean.

The decline in stock prices reflects investors' downgrading of the value of these banks' deposit franchises. Consistent with this interpretation, it is precisely low-density banks that experienced the largest deposit outflows in early 2023. We test the relationship between branch density and deposit flows during Q1 2023 using data from regulatory call reports. We find that banks within the lowest-density bucket are 13% more likely to fall into the top decile of net deposit outflows between Q4 2022 and Q1 2023 relative to those with density above 10. The higher likelihood of large outflows affects both insured and uninsured deposits. The decline across deposit types highlights how our branch density measure reflects a broader notion of sophistication and alertness among the depositor bases of low-density banks that goes beyond insured or uninsured status.

Our event studies control for mark-to-market losses, deposit-to-asset ratios, and other bank characteristics, isolating the independent effect of depositor composition on crisis performance. The fact that branch density predicts both stock returns and deposit outflows conditional on asset-side vulnerabilities suggests that the composition of the depositor base is itself a source of fragility.

We contribute to the literature on banks' deposit franchise by showing that branch density provides a new proxy for depositor sophistication that goes beyond regulatory categories. The theoretical literature emphasizes that banks serving alert, rate-sensitive depositors face greater run risk (Jiang et al. 2024, Drechsler et al. 2026, Blickle et al., 2025), but empirical implementations of such models typically use regulatory distinctions in deposits—for example, corporate versus household, insured versus uninsured, or brokered deposits—to proxy for differences in alertness. Branch density captures otherwise unobserved variation in sophistication and predicts crisis performance. Importantly, branch density is transparent, readily available, and straightforward to construct for all FDIC-insured banks.

We add to the literature on digitization in banking by highlighting how the move away from branches changes the allocation of financially and technologically sophisticated depositors across banks, which can have significant financial stability implications. While the existing literature highlights the pro-competitive effects of digital technologies on banking (Haendler (2022), Jiang, Yu, and Zhang (2026), Erel et al. (2025)), our evidence highlights an important trade-off; as banks compete for a financially and technologically sophisticated clientele, flighty depositors tend to concentrate in a narrow set of banks: low-density banks. Our findings on the heterogeneity and correlation in consumers' financial and technological sophistication also inform an important empirical moment that structural models of digital banks must match (Koont (2025), Koont, Santos, and Zingales (2025)). Namely, such models must allow for digitization to change the matching between heterogeneous depositors and banks and not simply change depositors' preferences.

The rest of the paper is organized as follows. Section I describes our data and provides summary statistics. Section II introduces and studies branch density in the U.S. banking sector. Section III analyzes the characteristics of depositors in low-density banks. Section IV discusses the business models of low-density banks. Section V documents the relation between branch density and stock returns and deposit flows during the 2023 banking crisis. Section VI concludes.

I. Data and Summary Statistics

We use several data sources to construct our measure of branch density,[1] understand the business model of low-density banks, and test how low-density banks performed in the 2023 banking crisis.

A. Data Sources

A.1. Deposits and Financial Data

To construct our main explanatory variable—bank branch density—we use data from the Summary of Deposits (SOD), an annual survey of branch-level deposits for all institutions insured by the Federal Deposit Insurance Corporation (FDIC). We include all deposit-taking branches, identified by branch service types 11, 12, 23, or 29, and aggregate their counts at the bank holding company (BHC) level. Dropping this restriction has minimal impact on our results: deposit-taking branches constitute more than 99% of branches.[2] For deposit volumes, we sum deposits across all branch types and aggregate to the BHC level. Branch density is then calculated as the number of deposit-taking branches divided by total deposits (in billions of dollars) at the BHC level. For simplicity, we use the terms "bank" and "bank holding company" interchangeably throughout.

We also extract the following financial variables from the quarterly Consolidated Reports of Condition and Income (call reports): total assets, insured deposits, total domestic deposits, corporate deposits, and number of deposit accounts, all at the bank level. These variables are then aggregated to the BHC level. Using the aggregated data, we construct the following measures: total domestic deposits as a fraction of total assets (*Dep/Asset*), insured deposits as a fraction of total domestic deposits (*Insured Dep/Total Dep*), deposit growth over the years 2019 to 2022 (*Dep Growth 2019–2022*), bank size (*log(Asset)*), corporate deposits as a fraction of total domestic deposits (*Corporate Dep/Total Dep*), and the average deposit account size, measured by taking the natural logarithm of the ratio of total deposits to the number of deposit accounts (*log(Avg Dep)*). Following Jiang et al. (2024), we measure mark-to-market (MTM) losses using call reports data on bank holdings of mortgages and treasuries, combined with changes in Treasury Bond prices and Mortgage-Backed Securities (MBS) Exchange Traded Funds (ETF). The data creation process is detailed in Appendix A.

[1] We note that while we define branch density as branches/deposits, the term is sometimes used in other context, such as branches/population or branches/area (Hirtle, 2007).

[2] Appendix A provides a description of each branch type.

A.2. Demographic Characteristics

We employ two data sources to measure banks' clientele. The first data source is the American Community Survey (ACS), which provides detailed social demographics at the county level. Specifically, we delineate four key variables: (1) *Urban,* denoting counties with populations exceeding 100,000; (2) *Log County Income,* defined as the natural logarithm of the median income in a county; (3) Age 60+, defined as the proportion of a county's population aged 60 or older; and (4) Higher Education, indicating the percentage of a county's populace holding a bachelor's degree or higher. Next, we formulate bank-specific clientele metrics as weighted averages of these county-level characteristics, with weights determined by the bank's deposits within each county. Since we do not observe the identities of individual bank depositors in these data, we presume that the demographic characteristics of the counties in which banks' branches are located are correlated with their depositor bases. Although these measures are arguably noisy for banks' depositor demographics, particularly for those that rely heavily on digital channels, it remains reasonable to assume that even low-density banks locate their branches near their customers' bases.

The second data source is the MRI-Simmons Ultimate Survey of Americans, a comprehensive, nationally representative survey of American consumers. This consumer-level dataset allows us to determine individuals' primary banking relationships, which we match to our measure of branch density. The MRI-Simmons data also provide granular sociodemographic information, including age, income, gender, and educational attainment. Importantly for our analysis, the dataset includes detailed behavioral information on how individuals interact with their banks. This encompasses whether they conduct banking activities online or in person, their use of mobile banking applications and digital payment methods, and their stated preferences and services they value in banking services. These detailed microdata enable us to identify consumers who are more sensitive to interest rate offerings and exhibit a strong preference for modern technology, key dimensions in assessing consumer responsiveness and financial decision-making. Unlike the county-level ACS data, which does not reveal individual depositors' identities, the microlevel MRI dataset provides detailed depositor-level information. This granularity enables us to observe and analyze individual depositor characteristics in relation to bank activity. By leveraging both the ACS and MRI datasets, we are able to demonstrate a strong association between the composition of bank clientele and depositor demographics and our measure of branch density.

A.3. Technology Measures

We use several data sources to measure banks' use of technology. First, we use the information technology (IT) investment data obtained from SWZD Aberdeen (originally known as Harte-Hanks). The dataset covers all industries and company sizes and was created by surveying establishments on their IT budgets. The data, which Aberdeen sells to technology companies for sales and marketing purposes, spans the years 2010 to 2017.[3] In 2018, Aberdeen changed the data collection methodology from surveys of IT budgets to imputations of IT investment using proprietary models, and so we use Aberdeen data only through 2017. We match Aberdeen's IT data to bank branches and then aggregate IT investment at the BHC level.

Second, we obtain data on bank website traffic from Semrush. Semrush is a leading digital marketing and SEO (search engine optimization) platform that provides tools for businesses, marketers, and SEO professionals to improve their online visibility. Semrush provides traffic analysis over the most recent seven months for a large and frequently updated sample of websites—especially those with notable search engine visibility or digital marketing activity. In May 2023, we manually searched the 2022 sample websites for publicly traded banks and collected monthly website traffic reports from October 2022 to April 2023 for 186 bank holding companies in the sample.

Third, we use granular job posting data from Lightcast to assess banks' labor demand and organizational intent. Lightcast compiles a near-comprehensive dataset of online job postings consistently from 2010 onward. We hand-match all bank holding companies in our 2022 sample to employers in the Lightcast database, yielding approximately 6 million job postings from 2010 to 2022. Each posting contains information on the employer, job title, posting date, and required skills. Each job reflects multiple dimensions through its required skills—for instance, a software engineer role typically involves software development and data handling, as indicated by core programming skills such as Java or Python, but may also include managerial tasks. To better gauge banks' skill demand and capture the variety of each job, we analyze all listed skills using a structural topic model (STM). This approach allows us to account for the multifaceted nature of

[3] See He et al. (2026) for a detailed description of the SWZD Aberdeen data. Other papers using the Aberdeen data include Bloom, Draca, and Van Reenen (2016) and Tuzel and Zhang (2021). Ahnert et al. (2026) use an alternative measure of banks' IT investment that results in a value of zero for the IT spending of many banks.

each job rather than relying on a simple tabulation of certain job types. We describe our implementation of STM and its application to job-skill data in Appendix A.2.

A.4. Deposit Rates

To measure the rates offered by banks we use RateWatch, which collects weekly deposit rates for various deposit products at the branch level. Our primary measure is the deposit rate for a 12-month certificate of deposit (CD) requiring a minimum deposit of $10,000 (12MCD10K). This product is well represented in the data and widely used in the literature. Alternatively, we also consider the rate for another commonly surveyed product: a 24-month CD with a minimum deposit of $100,000 (24MCD100K). We match the RateWatch branch-level data to branches listed in the Summary of Deposits. For the main cross-sectional analysis, we average the weekly rate observations across all branches within each bank for the entire year of 2022; for analyses over longer horizons, we use data at the bank-week level. To complement the RateWatch data, we also infer deposit rates from call reports by dividing interest expenses on domestic deposits by total domestic deposits.

A.5. Stock Prices

Last, to conduct event studies of the response of banks' stock prices to the failures of Silicon Valley Bank, Signature Bank, and First Republic Bank, we measure banks' stock returns around those events. SVB failed on Friday, March 10, 2023, and state regulators closed Signature Bank on Sunday, March 12, 2023. We obtain data on stock prices from CRSP (Center for Research in Security Prices) and measure returns as the change of the close price between March 8, 2023, and March 13, 2023. Similarly, for the second event—the collapse of First Republic Bank, which the California Department of Financial Protection and Innovation closed on Monday, May 1, 2023—we measure returns as the change in the close stock price between Friday, April 28, 2023, and Tuesday, May 2, 2023. We consider alternative time periods in robustness checks.

[Insert Table I Here]

B. Summary Statistics

Table I presents summary statistics for the main variables used in the analysis. The majority of variables are based on data from approximately 3,600 bank holding companies. Certain variables, however, are available only for smaller subsets of banks due to data limitations. Specifically, stock return data are reported for just over 300 publicly traded banks, while variables related to technology adoption and deposit pricing are observed for between 180 and 3,200 institutions, depending on dataset coverage. We provide detailed definitions of all variables in Appendix A.

The average (median) value of our key variable of interest, *branch density,* in 2022 equals 19.4 (14.9) in the full sample of all banks and 9.3 (9.1) in the sample of public banks. The histogram of branch density, which illustrates that larger public banks generally exhibit lower branch density than private banks, is presented in Figure 3. As of June 2022, a typical sample bank has a deposits/assets ratio of 86%, and 57% of its total deposits are FDIC insured. On average, corporate deposits account for 38% of total deposits in domestic offices, which is in line with the notion that uninsured deposits are more likely to be corporate deposits. During the Covid-19 pandemic, deposits increased by almost 50% between 2019 and 2022 in the average bank.

Following the collapse of SVB and First Republic Bank, the stock price of the average bank in our sample declined 13.3% and 6.9%, respectively. Despite the stress in the U.S. banking industry in Q1 2023, an average bank still experienced a 0.8% deposit increase relative to Q4 2022, but uninsured deposits declined by 2.7% on average. The average bank experienced 13.6% mark-to-market implied asset value losses between Q1 2022 and Q1 2023—stemming mostly from rising interest rates.

Banks allocated significant resources into information technology during the 2010s: IT budgets almost tripled between 2010 and 2017. For a typical job posted by a bank, 7.5% of required skills were technology-related, 26% customer-facing, 19% managerial, and 21% back-office. Website traffic to the average bank increased by 27% in March 2023 relative to February 2023. Deposit rates were still relatively low in the analyzed period, with the median bank paying a rate of 170 basis points on 12-month CD products and 10% of banks paying less than 30 basis points.

Almost 80% of bank customers use banking app, as measured in the MRI data. While over half of them says that they value branch location, 40% also says that they value the level of interest rates they receive. 7% of customers say they are likely to change their bank within the next 12 months.

II. The Decline of Bank Branches and the Rise of Deposits

The number of bank branches in the United States increased steadily until 2009 despite technological advances that enabled digital banking through banks' websites and apps (Anenberg et al. (2018)). Beginning in 2010, the number of bank branches declined annually, and the rate of decline accelerated over time, reaching around 2% annually in the second half of the 2010s and over 3% per year following the Covid-19 pandemic. By June 2022, the number of bank branches reached its lowest level since 2000 at 79,185, corresponding to a 20% reduction relative to the peak of 99,550 branches in 2009. Figure 1 depicts the decline in the total number of bank branches in the United States.

[Insert Figure 1 Here]

Figure 1, Panel A, also demonstrates that the decline in the number of bank branches was not accompanied by a decline in total deposits. In fact, between 2010 and 2022, total deposits in U.S. banks almost doubled in real terms, rising from $10.30 trillion in 2010 to $18.14 trillion in 2022, both in 2022 dollars. Deposits grew from $14.67 trillion in 2019 to $17.63 trillion in 2020, reflecting the increase in U.S. household saving rates and large government stimulus payments during the Covid-19 pandemic (Levine et al. (2021)).

[Insert Figure 2 Here]

Rising deposits and reductions in the number of branches resulted in higher levels of deposits per branch. We demonstrate the correlation between rising deposits and the declining number of branches in Figure 2. To construct the figure, we run the following bank-level (i) cross-sectional regressions of total deposits on the number of bank branches for all FDIC-insured banks in a given year *t*:

$$Deposits_i = \alpha + \beta \times Number\ of\ Branches_i + \epsilon_i. \qquad (1)$$

Figure 2 plots the R^2s from each of the cross-sectional regressions (left axis) as well as β— the coefficient on the number of branches in each regression (right axis). As illustrated by the dashed line in Figure 2, in 2010, each branch accounted for about $150 million (expressed in 2022 dollars) in deposits. Deposit levels per branch increased over time, and by 2022, a branch was associated, on average, with more than $325 million in deposits. As the solid line in the figure illustrates, the explanatory power of the number of branches in the deposits regressions has declined significantly over time. In 2010, the number of bank branches accounted for over 90% of variation in banks' deposits. By 2022, this explanatory power had fallen to less than 80%.[4]

[4] The decline in the number of bank branches is also evident in the bank-level regression. Table AII demonstrates that the decline happened among medium and large banks (columns (3) and (4)), whereas the number of branches of small banks grew (column (2)). On average, there are more than 600 branch closures a year during our sample period, with an additional 4,000 branch closures during the Covid-19 pandemic (column (1)).

Figure 3 plots the distribution of branch density in 2022 for all bank holding companies (blue) and for the subset of public bank holding companies (orange). The figure illustrates that public banks generally have lower branch density. Specifically, public banks in the lowest decile of branch density have fewer than two branches per $1 billion of deposits—with the bottom 5% banks having at most 0.15 branches per $1 billion of deposits. Across both distributions, branch density is highly skewed, with most banks concentrated at low levels and a long right tail. This distribution suggests that the economic effects of branch density are unlikely to be linear. Accordingly, we allow for nonlinearities by modeling branch density using indicator variables for density bins. We generally use five-unit bins, with finer cutoffs at the lower end of the distribution. Specifically, we classify banks into the following branch density categories: below 2.5, where 2.5 corresponds approximately to the 5th percentile of the full bank distribution and the 10th percentile among publicly traded banks, [2.5, 5), [5, 10), and greater than 10.[5]

[Insert Figure 3 Here]

Appendix Table AI shows examples of banks from each of the four groups of branch density as of 2022: density < 2.5, between 2.5 and 5, between 5 and 10, and above 10.

Appendix Figure A3 shows that decline in the branch density was most pronounced among large and medium-sized banks, although it occurred throughout the banking sector. Figure A4 compares deposit growth across banks with different branch densities. Since deposit growth itself influences branch density, the interpretation of a contemporaneous correlation between the two is problematic. To alleviate this concern, we classify banks into four branch density groups based on their 2010 density levels and keep the group composition fixed over time. Deposit amounts are expressed in 2022 dollars, and the average growth in total deposits (Panel A), insured deposits (Panel B), and uninsured deposits (Panel C) is plotted for each density group. The figure illustrates that deposit growth was significantly higher for low-density banks. The pattern is visible for both insured and uninsured deposits but is more pronounced for uninsured deposits.

The important role of uninsured deposits in driving the decline of low branch density is also depicted in Figure A5. The number of bank branches to *uninsured* deposits declined rapidly, in contrast to the number of bank branches to *insured* deposits, which stayed roughly unchanged.

[5] For further discussion, refer to Section V.A. (Figure 7).

Overall, the evidence presented shows that between 2010 and 2022, the number of branches of U.S. banks declined substantially relative to banks' total deposits, leading to declining branch density. Moreover, banks with the lowest branch density experienced faster deposit growth.

III. Depositor Characteristics at Low-Density Banks

Banks with lower branch density tend to attract depositor bases that are more technologically adept and financially sophisticated, including households that actively manage their savings and corporations with substantial funds available for deposit. This depositor base exposes low-density banks to deposit flightiness risk, especially when interest rates rise.

A. Corporate Deposits, Deposit Size, and Demographics

First, we relate depositors' characteristics to bank branch density using the following specification, where *i* indicates bank:

$$\begin{aligned} Y_{\mathrm{i}} \;=\; & \beta \times \sum_{b=1}^{3} Branch\ DensityBin_{i,b} + \\ & \alpha_1 \times \frac{Dep_i}{Asset_i} + \alpha_2 \times \frac{Insured\ Dep_i}{Total\ Dep_i} + \\ & \alpha_3 \times \mathrm{MTMLosses_i} + \alpha_4 \times \mathrm{Dep\ Growth}(2019-2022)_{\,i} + \\ & \alpha_5 \times \log(Assets)_i + \alpha_6 \times \mathrm{SizeBin_i} + \epsilon_i . \end{aligned} \tag{2}$$

Branch Density Bin consists of three indicator variables that equal one if a bank's branch density is below 2.5, between 2.5 and 5, or between 5 and 10, respectively. The omitted category comprises banks with branch density above 10. We additionally control for bank size measured by the logarithm of total assets and five size-quintile indicator variables. We control for deposits-to-assets ratio, for insured deposits scaled by total deposits, and for estimates of mark-to-market losses on banks' investment, constructed following Jiang et al. (2024). Last, to capture a potential effect of abnormal deposit growth in the years leading to the crisis, we control for the change in deposits between 2019 and 2022.

[Insert Table II Here]

In the first two columns in Panel A of Table II, we use corporate deposits as a fraction of total deposits and the average deposit amount per account (*log(Avg Dep)*) as dependent variables. As columns (1) and (2) illustrate, banks with lower branch density have a higher share of corporate deposits and larger average deposit amounts per account. Banks with branch densities below 2.5

have a deposit base that has 14 percentage points more corporate deposits, with an average deposit size that is over three times larger. Corporations and households holding substantial deposits are generally more sophisticated and vigilant regarding their investments. Consequently, their disproportionate presence among low-density banks' depositors renders these banks' deposits less stable during periods of uncertainty.

We use two data sources to measure personal characteristics of banks' clientele. The first is the American Community Survey (ACS), which provides detailed sociodemographic information at the county level. In columns (3)–(6) of Panel A we analyze the relation between bank-level proxies for clientele demographics and branch density. Using data from the ACS at the county level, we delineate four key variables: (1) *Urban,* denoting counties with populations exceeding 100,000; (2) *Log County Income,* defined as the natural logarithm of the median income in a county; (3) *Age 60+,* defined as the proportion of a county's population aged 60 or older; and (4) *Higher Education,* indicating the percentage of a county's populace holding a bachelor's degree or higher. Next, we formulate bank-specific clientele metrics as weighted averages of these county-level characteristics, with weights determined by the bank's deposits within each county.

The results reported in columns (3)–(6) suggest that banks with low branch density tend to have customers who are more likely to live in an urban area and are richer, younger, and more highly educated. The disparities observed in clientele attributes between banks categorized as low- and high-branch density are significant. Banks with very low densities have a depositor base that is over 25 percentage points more likely to be urban, with 16% higher income, with a 2 percentage point lower probability of being over the age of 60, and a 9 percentage point higher probability of having a college degree. These estimates are economically large, in that they correspond to an approximately 60% increase in the urban share, three-quarters of a standard deviation increase in income, a 10% increase in the county-level share of persons above age 60, and a 50% increase in the chance of having a college degree.

One concern with using ACS data is that it does not provide information on the identities of individual bank depositors. Instead, we assume that the demographic characteristics of the counties where a bank's branches are located reflect those of its depositors. As a result, our ACS-based variables are noisy proxies for the true demographics of a bank's clientele—especially for banks that rely heavily on digital banking and may attract depositors from outside their immediate geographic footprint. The ACS data thus cannot separate geographic sorting of banks and the demographic sorting of depositors.

To address these issues and to improve on the limitations of the ACS data, we use the MRI-Simmons Ultimate Survey of Americans (MRI) to better identify the characteristics of bank clientele. The MRI is a comprehensive, nationally representative survey of American consumers that includes detailed information on individuals' primary banking relationships. By linking these relationships to our measure of branch density, we can more accurately assess the demographic profiles of individual bank customers.[6]

Panel B of Table II replicates the analysis in columns (3)–(6) of Panel A using similar sociodemographic variables based on the MRI data. Across consumers j at banks i, we estimate the following regression specification:

$$Y_{ij} = \beta \times \text{BranchDensity}_{\text{i}} + \alpha_{\text{z}} + \epsilon_{ij}. \quad (3)$$

where α_z are three-digit zip code fixed effects. The dependent variables Y_{ij} are defined as follows: (1) Log Income is the natural logarithm of the depositor's household income; (2) *Age 60+* is an indicator for respondents aged 60 or older; and (3) *Higher Education* is an indicator variable for depositors who have attained a bachelor's degree or higher. The analysis is based on 63,252 observations from the 2021 and 2022 survey waves of the MRI Ultimate Survey of Americans.

The economic magnitudes are large. In our sample of public banks used in the event study analysis, the standard deviation of branch density is approximately 5. Panel B shows that, within three-digit zip codes, a one-standard deviation increase in branch density is associated with a 10 percent decrease in household income, a 19 percent increase in the share of depositors aged 60 and over, and a 7 percent decrease in the likelihood of having a bachelor's degree or higher. These quantitative magnitudes exceed those obtained from the ACS, which, by construction, cannot directly observe the demographics of clients at low-density banks and must rely instead on local-area demographic characteristics as a proxy. These results paint a clear picture: banks with a

[6] The survey collects information on consumers' primary banking relationships by asking respondents to identify the main bank they use. Participants are presented with a list of 13 large national banks. In addition to these named institutions, the survey includes broader categorical options such as "other national bank" and "other internet bank." We focus on the 13 named banks and the "other internet bank" category. For the 50% of consumers who list only one banking relationship among these banks, we assign that as the consumer's bank. For those who list multiple, we randomly assign them to one of the banks they list.

smaller physical footprint cater to a younger, more highly educated, and more affluent clientele, and this sorting goes beyond geographic sorting.

B. Other Dimensions of Financial and Technological Sophistication

Whereas prior research has relied on demographic characteristics as proxies for financial sophistication, a key advantage of the MRI data is its rich behavioral detail on how individuals interact with their banks and what they value when selecting financial institutions. Specifically, the data capture whether transactions are conducted online or in person, the extent of mobile banking app and digital payment platform usage, and consumers' stated preferences for various banking and payment services.

We use additional measures of rate sensitivity and technology adoption to show directly that the depositors who choose low-density banks tend to be more sensitive to rates and more eager to adopt new technologies. We estimate the following specification:

$$Y_{ijz} = \beta \times \text{BranchDensity}_{\text{j}} + \gamma \text{X}_{\text{j}} + \alpha_z + \epsilon_{ij}, \quad (4)$$

where Y_{ij} is a behavioral outcome for individual *j* at bank *i* in three-digit zip code z, X_{j} is a vector of the demographic controls (Log Income, Age 60+, Bachelor's), and α_{z} are three-digit zip code fixed effects.[7] By including these additional controls and fixed effects, we show that these low-density banks have a particularly financially and technologically sophisticated clientele that is not fully captured by traditional sociodemographic characteristics.

The first three columns of Table III explore how branch density correlates with three measures of rate sensitivity, which we rescale by a factor of 100: (1) "Values Interest" equals 100 if the consumer reports that interest rates are very important when choosing a bank or financial institution, and zero otherwise; (2) "Money Market" is equals 100 if the consumer reports owning money market funds, and zero otherwise; and (3) "Likely Change Banks" equals 100 if the consumer reports being somewhat or very likely to change to another bank in the next 12 months, and zero otherwise.

[7] We employ three-digit zip code fixed effects due to limited sample size in the survey data, which does not allow for a reliable identification of variation within five-digit zip code level.

[Insert Table III Here]

Depositors at low-density banks are more rate sensitive both because they tend to have demographic characteristics correlated with higher rate sensitivity and because consumers with an especially high sensitivity to interest rates sort to the low-density banks. The estimated coefficients on the controls in column (1) show that higher-income, younger, and more highly educated depositors are more likely to say that interest rates are an important factor when choosing a bank. As previously shown in Table II, the low-density banks attract exactly this clientele. This demographic channel is one reason that low-density banks serve rate-sensitive clienteles. However, the negative coefficient on branch density means that even within demographic groups and geographies, consumers who opt for low-density banks are particularly sensitive to interest rates. The economic magnitude of this residual branch density effect, even conditional on demographics, is large. When scaled by the mean of the dependent variable, a one standard deviation increase in branch density corresponds to an approximately 19% decrease in the probability that a consumer reports interest rates as an important factor when choosing a financial institution. This means that low-density banks serve a clientele whose rate sensitivity is higher than demographics alone would predict, which reflects traditionally unobservable variation in preferences for deposit rates.

Columns (2) and (3) use two additional measures of rate sensitivity to show that demographic characteristics and consumer sorting contribute to high-rate sensitivity at low-density banks. Column (2) shows that higher-income and more highly educated depositors are more likely to invest in money market funds, a natural alternative to bank deposits (Xiao (2020)). Thus, depositors at low-density banks are more likely to invest in such an alternative. On top of that, a one-standard deviation increase in branch density predicts a 14% decrease in the probability of investing in a money market fund. Similarly, the third column shows that younger depositors are more likely to switch banks. But even conditional on demographics, a one-standard deviation increase in branch density predicts a 30% lower probability of a consumer reporting that they are likely to change banks in the upcoming year.

The last three columns of Table III investigate three measures of financial technology adoption. “Values Location” equals 100 if the consumer reports that branch location is very important when choosing a bank or financial institution, and zero otherwise; “Banking App” equals 100 if the consumer reports accessing their bank account via a mobile app in the past 12 months, and zero otherwise; and "Payment App" equals 100 if the consumer says that they have used Zelle, Venmo, or Cash App in the past 30 days, and zero otherwise.

Both demographics and consumer selection explain why depositors at low-density banks are more likely to adopt new financial technologies. The controls in column (4) show that older borrowers are much more likely to say that they value branch location when choosing a bank. Although higher-income individuals are also more likely to report valuing branch location, the size of the coefficient on branch density is smaller than the analogous effect of income on whether consumers value interest rates. On top of the demographic effects, however, depositors who sort into low-density banks are less likely to report valuing location. Conditional on demographics, a one-standard deviation increase in branch density predicts an approximately 15% increase in the share of consumers reporting that they value branch location. Similarly, columns (5) and (6) show that it is precisely the high-income, young, and more highly educated depositors who are more likely to adopt mobile banking and fast-payment apps. This implies that the clientele of low-density banks is already more inclined to adopt technologies that facilitate deposit outflows (Lu, Song, and Zeng (2025)). But on top of those demographic effects, incremental increases in branch density are associated with lower technology adoption. A one-standard deviation increase in branch density predicts an approximately 9% decrease in the share of consumers using mobile banking and a 17% decrease in the share of consumers adopting fast-payment apps.

[Insert Figure 4 Here]

Figure 4 illustrates that the differences between depositors at high- and low-density banks extend to a much wider range of measures of financial sophistication. The figure plots the results of specification (4), in which we regress different depositor characteristics on the branch density of their bank, controlling for both demographics and three-digit zip code fixed effects. Each point reflects the percentage change in various outcomes for a one-standard deviation increase in branch density, and each interval is the 95% confidence interval. The results indicate that depositors at lower-density banks are more financially sophisticated: they hold 22% more credit cards and are 12% more likely to own stocks. The higher use of credit cards appears to reflect demand, and not supply, since the credit scores of consumers at high- versus low-density banks are similar. Depositors at low-density banks are also more engaged with financial markets, as shown by their 14% higher propensity to read financial news, 10% higher likelihood of reporting that they shop for the best deals when choosing financial services, and 8% higher use of social media platforms such as Twitter/X.

Our analysis finds that sorting of depositors across banks with different business models goes above and beyond what observable demographics can explain. This implies that low-density banks attract a clientele that is more rate sensitive not just because of their age or income but also because of such unobservable traits as higher financial sophistication, a greater attentiveness to financial markets, or a stronger innate preference for digital channels.

C. Within-Bank Results

Although our results show that branch density is highly predictive of bank clientele, they leave open the possibility that the relationship is explained by other unobserved bank characteristics that are correlated with branching strategy. To more credibly isolate the effect of physical branch presence from other bank-level characteristics such as advertising strategies or asset losses, we shift our analysis from the bank-level *Branch Density* measure to a more granular measure of a bank's local footprint. Specifically, we examine the impact of the number of branches of a consumer's chosen bank in their local three-digit zip code. We construct this measure with data from the summary of deposits. We focus on three-digit zip codes because they cover a larger area than five-digit zip codes and because consumers may travel across the usual five-digit zip code areas to access banking services. This allows us to exploit the substantial spatial variation in the branch networks of large banks to understand how the taste for branches relates to interest rate sensitivity and technological sophistication in the population of depositors.

Across depositors j at banks i in three-digit zip codes z, we estimate

$$Y_{ijz} = \beta \times \#Local\ Branches_{iz} + \gamma X_j + \alpha_z + \alpha_i + \epsilon_{ij}, \tag{5}$$

where α_z and α_i are zip code and bank fixed effects. For interpretability, we standardize the number of local branches by the within-zip-code standard deviation of the number of branches across banks. Formally, we first regress the number of branches of consumers' chosen banks on three-digit zip code fixed effects. We then divide the number of branches by the standard deviation of the residual of this regression. In these specifications, we drop online banks because they have no variation in branch presence across geographies. This reduces our sample to 54,296 depositors.

The addition of bank fixed effects is a powerful identification tool that controls for all unobservable, time-invariant bank-level characteristics (e.g., asset losses). By including both zip code and bank fixed effects, the model compares depositors of the *same bank* who live in *different zip codes* and thus are exposed to a different number of local branches while also controlling for patterns common to all residents of a given zip code. Intuitively, if we observe, for example, two Citibank customers, the first of whom chooses Citibank in an area with many Citibank branches and the second of whom chooses Citibank in an area with few Citibank branches, then the first consumer is more likely to have a taste for branches independent of their taste for other bank characteristics. By comparing the interest rate sensitivity and technology adoption of the two groups of depositors, we can understand how much consumers' preferences for branches correlate with their preferences for deposit rates and new technologies.

[Insert Table IV Here]

The first three columns of Table IV show that even within banks, consumers who are more likely to prefer branches are also less sensitive to interest rates. Column (1) shows that even within banks and three-digit zip codes, depositors who are exposed to one standard deviation more branches tend to have a 3% lower probability of saying that they consider interest rates as very important when choosing a bank. Similarly, column (2) shows that a greater local branch presence is associated with a 5% lower probability of investing in money market funds and a 14% lower probability of being likely to change banks in the upcoming year. Although it is difficult to map the quantitative magnitude of these results back to branch density, these results highlight how even within banks there is a negative relationship between the taste for branches and sensitivity to interest rates.

The next three columns of Table IV examine within-bank patterns in technology adoption and preferences for branch location and find a negative, albeit weaker relationship. Column (4) finds a slightly negative and statistically insignificant relation between branch exposure and the likelihood that the consumer reports that branch location is important when choosing a bank. Columns (5) and (6) show that a one-standard-deviation increase in local branches is associated with a 1%–2% decrease in the use of both banking and fast-payment apps, both with and without bank controls. These results suggest that valuing location is a stable preference of customers who select into high-density banks (a between-bank effect), rather than a reaction to the number of branches in their immediate area (a within-bank effect).

Financial and technological sophistication are highly correlated, even within banks. Panel B of Table AIII regresses depositor-level measures of rate sensitivity on technological sophistication, including three-digit zip code and bank fixed effects to ensure that comparisons are made among depositors at the same bank. Rate sensitivity is measured as a binary indicator for whether the depositor reports that interest rates are important when choosing a bank; technological sophistication is the average of two indicators for mobile banking use and fast-payment app adoption (Zelle, Venmo, or Cash App). Depositors who are more technologically sophisticated are also more sensitive to deposit rates. This relationship persists with and without demographic controls, which explain roughly 20% of the effect. The reverse relationship is equally strong: rate-sensitive depositors exhibit higher technological sophistication.

D. Other Dimensions of Technological Sophistication

Although the quality of banks' digital experiences may influence some aspects of financial technology adoption across consumers, the survey data highlight that the depositors at low-density banks also differ in how they use technology in nonfinancial domains. Panel C of Figure 4 reveals a strong preference for traditional service channels; depositors at low-density banks are 13% less likely to purchase car insurance through an agent and 18% more likely to purchase car insurance online. Panel D of Figure 4 shows that they are also earlier adopters of nonfinancial technologies. They are 12% more likely to use online real estate listing services such as Zillow or Redfin, 11% more likely to drive an electric or hybrid vehicle, and 6% more likely to listen to podcasts.

E. Summarizing the Demand-Side Facts

Our analysis indicates that low-density banks serve a distinct clientele: depositors who are younger, wealthier, more highly educated, more sensitive to interest rates, more likely to invest in money market funds, and quicker to adopt new financial technologies. Importantly, these patterns hold even within geographies and even within banks, suggesting that the relationship reflects sorting on preferences. The results on their adoption of nonfinancial technologies also highlight how depositors at low-density banks are particularly selected. We turn next to examining the supply-side decisions that banks make to attract this sophisticated clientele.

IV. The Business Model of Low-Density Banks

The previous section documented that depositors at low-density banks are more financially and technologically sophisticated than their counterparts at high-density banks. A natural question is whether this sorting reflects deliberate bank strategy. In this section, we examine supply-side decisions—technology investments, hiring practices, and deposit pricing—to understand how low-density banks compete for sophisticated depositors. We find that these banks invest more heavily in IT, prioritize technical skills over customer service in their hiring, and offer higher deposit rates. These strategic choices follow naturally from the structure of consumer preferences. Because financial and technological sophistication are correlated among consumers, banks that invest in digital platforms face strong incentives to offer competitive rates.

A. Technology

To investigate the role that digital technology plays in the business strategies of banks with low branch density, we test the relation between branch density and IT investment using a design similar to specification (2). Column (1) in Table V shows a positive correlation between increases in IT investment between 2010 and 2017 and low branch density in 2022. Specifically, IT investment growth was 38 percentage points higher for banks with a branch density below 2.5, and 30 percentage points higher for banks with density between 2.5 and 5, relative to the control group of banks with density above 10. These differences constitute 10%–15% of the average growth of IT investment between 2010 and 2017, which was almost 300%.

[Insert Table V Here]

Digital banking can enhance banks' ability to attract deposits during normal market conditions by offering convenience, broader geographic reach, and user-friendly interfaces. However, digital banking may also fundamentally change the composition of banks' depositor base through two related channels. First, digital platforms often attract more rate-sensitive, more transaction-oriented, or less relationship-driven customers. These depositors could be corporations with large uninsured deposits and sophisticated individuals who closely follow financial news via digital media and respond quickly to market developments. As a result, during periods of financial distress or market uncertainty, these depositors may be more prone to flee. Second, digital service by nature allows clients to transact quickly and with little friction, enabling depositors to withdraw at their (literally) fingertips. In this way, digital banking, while beneficial in stable times, may make banks' deposit base more mobile and reactive during stressed episodes.

Although the results presented in column (1) of Table V suggest a link between lower branch density and higher IT spending, which may negatively affect the stability of deposits, there are two concerns regarding the validity of this correlation. First, it is likely that all banks in the sample provide online banking services, regardless of their branch density, potentially weakening the distinction between low- and high-density institutions in terms of digital capabilities. Second, the association between large IT budgets and reliance on digital customers is not unequivocal, since IT expenditure may encompass a range of operational banking services unrelated to deposit management.

To address both empirical challenges, we use data on web page traffic on banks' websites at the end of 2022 and beginning of 2023 as a more direct measure of customer-oriented digital banking exposure and usage.

[Insert Figure 5 Here]

Figure 5 displays the coefficient from regressing the natural logarithm of the number of web page visits on indicator variables for each month between November 2022 and April 2023 and bank fixed effects. The sample starts in October 2022, which is the omitted category. When Silicon Valley Bank and Signature Bank collapsed in March 2023, online traffic was on average 15% higher than in October 2022. And although, as evident from the figure, website traffic in each of the first four months of 2023 was somewhat elevated, the coefficients are not statistically significant for any other month except March, which also displays a jump relative to February. This pattern demonstrates that a modern banking crisis may have less to do with depositors queuing outside bank branches and more to do with depositors flooding bank websites to transfer their money online. Online money transfer to other banks is faster and more convenient, which is especially important when depositors are concerned about the safety of their deposits. Online banking thus makes running on a bank easier.

We analyze the relation between web page traffic and branch density and report the results in tabular form in columns (2) and (3) of Table V. As shown in column (2), banks with lower branch density experienced significantly greater increases in web traffic in March 2023 relative to February 2023. Banks with density below 2.5 experienced an additional 72.7% increase in traffic in March relative to the control group, which is more than double the average February-to-March increase of 27.5% for all banks. The coefficients for banks with intermediate density levels are also positive but insignificant.

In column (3) of Table V, we scale online traffic by total deposits to demonstrate that the level of web traffic was elevated for low-density banks not only during the crisis but also throughout the sample. The traffic-to-deposits ratio is 5 percentage points higher for the lowest-density banks, although this coefficient is only marginally significant.

Last, we study banks' reliance on technology by analyzing their labor demand using job posting data from Lightcast. Our measures of banks' skill demand are based on structural topic model (STM) scores from approximately 6 million Lightcast job postings. STM is an unsupervised machine-learning method that identifies latent thematic structures (topics) within text data. We set the number of topics to 25 to strike a balance between minimizing model residuals and maximizing thematic coherence. To understand the model-identified topics and map them into conceptually interpretable categories, we rely on the use of high-probability words (skills in our application) within each topic. These skills are the words most likely to appear in a given topic, and they tend to reflect the core, common vocabulary of that topic. The top five most frequently listed skills within each topic, along with an exemplary job posting, are reported in Appendix A. For each job posting, the STM assigns topic scores that sum to 100, reflecting the relative importance of each topic in the job's skill requirements. The example job reported in Appendix A requires the following skills: Scrum, Non-Verbal Communication, Information Technology, Management, Prioritization, Agile Methodology, Business Valuation, Communication, Collaboration, Sprint Planning, Sprint Retrospectives, New Product Development, and Computer Science.

Based on the high-probability words, we further classify the topics into six broader categories: Technology (e.g., *information technology, data management, software development,* and programming languages such as *Java* and *SQL*), Back-office (e.g., *auditing, risk analysis,* and *clerical work*), Customer-facing (e.g., *customer service* and *sales*), General (e.g., *writing* and *communication*), Management (e.g., *management* and *leadership*), and Other (e.g., *investment, underwriting,* and *commercial lending*). For example, our categorization implies that the sample job described in Appendix A scores 63 on Technology and 16 on Management, indicating that 63% and 16% of its required skills are associated with technology and management, respectively, with low scores on all other topics.

To construct a bank-year-level measure, we average topic scores across all job postings for a given bank. Thus, a Technology score of 7.5% indicates that, on average, 7.5% of the skills required in a bank's job postings are technology related. In 2022, as reported in Table I, the average bank allocates approximately 7.5% of required skills to Technology, 26% to Customer-facing, 19% to Management, and 21% to Back-office categories, with the remaining 26.5% classified as Other. Our final sample includes 274 publicly traded banks with at least 150 observed job postings.

Panel B of Table V shows that lower branch density is associated with greater demand for technology skills and lower demand for customer-facing skills. Banks with the lowest branch density (<2.5) demand 10.6 percentage points more technology skills (significant at the 1% level), while those with branch density between 2.5 and 5 demand 3 percentage points more (also significant at 1%). These effects are economically large, given the 7.5% sample average share of technological skills required. In contrast, lowest-density banks demand 16 percentage points less customer-facing skills (significant at 1%), and those with branch density between 2.5 and 5 demand 7 percentage points less. Again, these are sizable effects relative to the 26% sample average for customer-facing skills. The results confirm that the business model of low-density banks relies heavily on digital technologies to replace traditional customer-facing service.

Columns (4) and (5) of Panel B of Table V show that there is no relation between branch density and the requirement for back-office and general skills. In contrast, banks with lower branch density exhibit significantly higher demand for management-related skills (column (3)). This pattern is consistent with greater organizational centralization and relatively higher employment at headquarters. With fewer employees serving customers in physical branches, management roles located at headquarters account for a larger share of total bank personnel.

Taken together, the patterns in IT investment budgets, web page traffic, and job postings skill demands all confirm a consistent relationship between branch density and banks' propensity to rely on digital technologies. This reliance on technology may thus be shaping the clientele of low-density banks and contributing to the greater mobility of depositors in times of crisis.

B. Deposit Rates

To attract a sophisticated clientele, banks with low branch density offer higher deposit rates. To the extent that financially savvy depositors are more price sensitive, they may be willing to forgo the convenience of a larger bank network in exchange for the ability to earn higher interest.

[Insert Table VI Here]

Table VI analyzes the relation between branch density and deposit rates. The main data on rates are obtained from RateWatch, which provides weekly surveyed deposit pricing at the branch level. We first match weekly deposit rates at the branch level to banks and then aggregate to the bank holding company level by taking a simple average. We analyze the average of all 2022 weekly rates for 12-month and 24-month CD deposits with deposit amounts of $10,000 or above (12MCD10K) and $100,000 or above (24MCD100K). We also analyze the deposit rate inferred from call reports by dividing interest expenses by deposits. Similar results are obtained for other maturities and deposit amounts.

Columns (1) and (2) demonstrate that banks with low branch density pay, on average, higher deposit rates. Banks with density below 2.5 pay rates that are 42–48 basis points higher, amounting to about 25% of the sample mean rates on similar maturities and deposit amounts for all banks, and more than 100% of the mean rates among public banks, among which many offer near-zero deposit rates. Column (3) confirms that low-density banks tend to pay higher deposit rates using an alternative way of measuring deposit rates based on call reports, that is, dividing total value of interest expenses by the total value of deposits. Taken together, the results confirm that more attractive deposit pricing is another factor that differentiates low-density banks from typical banks and a possible element of a business strategy that attracts more price-sensitive, but also more mobile, depositors.

C. Summarizing the Supply-Side Facts

Taken together, the evidence on technology investment, hiring practices, and deposit pricing reveals a coherent business strategy. Low-density banks compete for sophisticated depositors along multiple dimensions simultaneously. Because financial and technological sophistication are correlated among consumers, these strategic choices reinforce each other: banks offering superior digital platforms find it profitable to offer competitive deposit rates, and vice versa. Consistent with this, IT investment growth, deposit rates, and demand for technical skills are all positively correlated across banks (Table AIII, Panel A). A key implication is that, in equilibrium, low-density banks concentrate precisely those depositors most likely to flee during periods of financial stress. The regional bank failures of March and May 2023 provide a natural test of whether this concentration translates into measurable fragility.

V. Branch Density and Bank Fragility During the 2023 Banking Crisis

The previous sections document that low-density banks attract financially and technologically sophisticated depositors by offering competitive rates and investing heavily in digital platforms. The theoretical literature predicts that such banks face greater run risk: their insured depositors may leave when deposit spreads rise, while their uninsured depositors—more attentive to financial news and bank solvency—may flee at the first sign of trouble. The regional bank failures of March and May 2023 provide a natural test of whether this concentration of sophisticated depositors translates into fragility. In this section, we examine whether low-density banks experienced worse stock market performance and larger deposit outflows during the crisis.

A. Stock Returns During the 2023 Hiking Cycle

During the 2010s, U.S. banks were able to grow their deposits with fewer branches, and deposit growth was highest for banks with low initial branch density (Figure A4). However, although low-density banks were able to attract deposit inflows before 2023, they experienced significant difficulties during the first several months of 2023. In March 2023, two medium-sized American banks failed: Silicon Valley Bank and Signature Bank. Consequently, many banks suffered large stock price declines in March and April, and eventually a third bank, First Republic Bank, whose shares fell by 62% on March 13, 2023, suffered significant liquidity problems, leading to its closure and the disposal of its assets to JPMorgan Chase Bank.

Interestingly, as illustrated in Appendix Figure AI, all three troubled banks had extremely low branch densities before the crisis. Silicon Valley Bank had just 17 branches and about $175 billion in deposits—denoting a very low branch density of 0.097. Similarly, the branch densities of Signature Bank and First Republic were 0.36 and 0.53, respectively.

We conjecture that low branch density, reflecting the combination of deposit growth with limited branch expansion, contributed to the banking calamity in 2023. Clearly, multiple factors affected these banks, including interest rate risk mismanagement and, in some cases, exposure to the cryptocurrency sector. Our argument is not that low branch density itself caused these bank failures. Rather, low branch density serves as an indicator of the nature of these banks' business model and the resulting depositor bases, which were more likely to be financially and technologically sophisticated and therefore more prone to withdraw funds rapidly once concerns emerged. In this sense, what had previously been a virtuous cycle of deposit growth may have turned into a vicious cycle when depositor confidence deteriorated.

To test our conjecture, we conduct an event study around the March failures of Silicon Valley Bank and Signature Bank. Panel A of Figure 6 exhibits the relation between bank branch density and stock returns between March 8, 2023, and March 13, 2023. The sample includes all 324 publicly traded bank holding companies with branch and stock price information available. As demonstrated in the figure, there is a positive and significant relation between stock returns and bank branch density during the collapse of SVB. Some banks, such as PacWest and Western Alliance, performed particularly poorly, and they, too, were characterized by very low branch density.

[Insert Figure 6 Here]

To complement our analysis of the Silicon Valley Bank collapse, we conduct a second event study on the failure of First Republic Bank, focusing on bank stock returns from April 28, 2023, to May 2, 2023. Although the market reaction during this episode was comparatively less severe—likely reflecting the partial incorporation of information about banking sector vulnerabilities into stock prices following the collapse of SVB—this event nonetheless offers valuable context for examining the role of branch density. Panel B of Figure 6 depicts the density-return relationship during the First Republic episode, which exhibits a similar shape to that for the SVB episode.

To formally explore the relation between branch density and stock price performance during the 2023 banking crisis, we conduct a multivariate analysis of banks' stock returns during the two events of bank failures in March and May 2023. Specifically, we run the following regressions:

$$\begin{aligned} \mathrm{Return_i} \quad = \quad & \beta \times \mathrm{BranchDensity_i} + \alpha_1 \times \frac{Dep_i}{Asset_i} + \alpha_2 \times \frac{Insured\ Dep_i}{Total\ Dep_i} + \\ & \alpha_3 \times \mathrm{MTMLosses_i} + \alpha_4 \times \mathrm{Dep\ Growth(2019-2022)}_{\,i} + \\ & \alpha_5 \times \log(Assets)_i + \alpha_6 \times \mathrm{SizeBin_i} + \epsilon_i, \end{aligned} \tag{6}$$

where return is defined as in Figure 6. Branch density is either a linear term or a vector of four binary indicators for density below 2.5, between 2.5 and 5, between 5 and 10, and above 10. In addition, the controls are the same as those in equation (2). The results are presented in Table VII.

[Insert Table VII Here]

We uncover a positive and statistically significant relation between bank branch density and stock returns around the SVB collapse without (column (1)) and with (column (2)) control variables. The coefficients on the linear term of branch density are also economically significant. Using the estimates in column (2), a one standard deviation lower branch density (5.88) corresponds to around 2.8 percentage points (= 5.88 * 0.474) lower returns around the collapse of SVB, which represents approximately 21% (= −2.8%/−13.3%) of the sample mean of stock returns.

[Insert Figure 7 Here]

The event study results reveal a nonlinear relationship between branch density and stock returns, with the effects concentrated among banks with low branch density (recall Figure 6). Figure 7 illustrates this nonlinear relationship by plotting coefficient estimates from regressions analogous to those in Table VII with an extended set of binary indicators for different values of branch density. Specifically, we classify banks into the following branch density categories: below 2.5, where 2.5 corresponds approximately to the 5th percentile of the full bank distribution and the 10th percentile among publicly traded banks, [2.5, 5), [5, 10), [10, 15), [15, 20), and greater than 20. The resulting coefficient pattern reveals a clear nonlinear relationship, with stock returns increasing monotonically with branch density up to a level of 10, beyond which the marginal effect of additional branches diminishes. Figure 7 thus provides further evidence of the nonlinearity in the effect of branch density on returns. The pattern motivates our use of the nonlinear specification as the primary specification in the analysis when feasible, in which we group banks with branch density above 10 into a single category.

Formally, as shown in column (3) of Table VII, banks in the lowest density category experience the most pronounced negative stock market reaction, with average returns over 11 percentage points lower than those of the high-density reference group (i.e., those with density above 10). Banks with moderate branch density levels—between 2.5 and 5, and between 5 and 10—also show negative but smaller return differentials of 5.8 and 1.8 percentage points, respectively. All estimated coefficients are statistically significant.

In columns (4) and (5) of Table VII, we examine the relation between bank branch density and stock returns during the failure of First Republic Bank. We find that a one standard deviation decrease in branch density is associated with a 1.2 percentage point decline in stock returns (calculated as 5.88 × 0.203), which amounts to approximately 17% of the sample mean return of –6.9%. This magnitude is comparable to the effect observed during the Silicon Valley Bank episode, suggesting a consistent pattern across distress events. Furthermore, in the nonlinear specification presented in column (5), returns continue to increase monotonically with branch density. However, the evidence for nonlinearity is less pronounced in this episode compared to the case of SVB.

As for the effects of the control variables: banks with higher ratios of deposits to assets experience lower returns. A higher share of insured deposits, which implies a more stable base, is associated with higher returns. Banks that suffered higher mark-to-market losses have significantly lower stock returns after the First Republic collapse, with an effect of one standard deviation change being similar in magnitude to the effect of branch density.

In summary, our results show that banks with low branch density performed significantly worse during the two episodes of bank collapses, which we interpret as evidence that the financial markets perceived their deposits to be less stable and therefore viewed them as more vulnerable to deposit flight. In the next section, we test whether low branch density was indeed associated with large deposit outflows during the crisis.

B. Deposit Flows

The decline in stock prices reflects investors' downgrading of the value of low-density banks' deposit franchises. If this interpretation is correct, we should observe that these banks experienced larger deposit outflows. We test this prediction between branch density and deposit flows during Q1 2023 using bank regulatory data and a specification in the spirit of equation (6).

The dependent variable $Deposit\ Outflow_i$ is a binary indicator for a large negative net change in uninsured or insured deposits between Q4 2022 and Q1 2023. These indicator variables take the value of one for changes that are below the 10th or 25th percentile of the deposit flow distribution, and zero otherwise. All explanatory variables are the same as in specification (6) in the previous section. Table VIII reports the results.

[Insert Table VIII Here]

Columns (1)–(4) in Table VIII demonstrate that banks with the lowest branch density are significantly more likely to experience a large net outflow of deposits, both insured and uninsured. The result holds whether we define large net outflow of deposits as being in the lowest 10% or lowest 25% of the deposit flow distribution. The magnitudes of the observed effects are large: the probability of experiencing a large deposit outflow is 13–16 percentage points larger for banks with branch density below 2.5 relative to those with branch density above 10. Given that, by definition, the unconditional probability for an average bank is 10% or 25%, the effect is substantial. The effects are nonlinear and concentrated in the lowest density group, although an elevated probability of uninsured deposit outflows can also be observed for banks with density between 2.5 and 5.

The deposit outflows of 2023 represent a sharp reversal of the deposit growth that low-density banks had enjoyed in the preceding decade. Figure A4 shows that banks in the lowest density group quadrupled their deposits between 2010 and 2022, far outpacing all other groups.

The results on stock returns and deposit outflows are robust to alternative definitions and specifications. Table AIV demonstrates robustness to alternative definitions of branch density, which use (i) uninsured or (ii) brokered deposits instead of total deposits.[8] All measures yield similar results to those obtained in the main specification. While our baseline specification already controls for several factors contributing to bank performance (e.g., bank size (Caglio et al. (2024) or mark-to-market losses (Jiang et al., 2024)), in Table AV we show robustness to the inclusion of additional controls. Consistent with previous literature, we find that profitability before the crisis (Meiselman, Nagel, Purnanandam (2023)), cash ratio, and expected shortfall (Acharya et al. (2017)) predict banks' stock returns, but the effect of branch density remains significant. We do not detect a significant correlation of returns with share of nonperforming loans, commercial real estate loans, or supply-driven deposit flows (Gelman and MacKinlay (2026)) nor with within-bank concentration of deposits (Kundu, Park, and Vats (2025)).[9]

Our baseline time window to measure stock returns around the Silicon Valley Bank collapse is March 8 to March 13, which is motivated by the dynamics of stock market response to the crisis.[10] In Table AVI we present results analyzing other time windows. Both the magnitudes

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[8] For each measure, we construct four density quintiles following the approach in Table VII, columns (3) and (5). Since the magnitudes of the density variables differ across measures, the corresponding threshold values are specific to each measure.

[9] Some controls are available for all banks, while others apply only to public banks; accordingly, Table AV reports two sets of results. In both cases, the coefficients on branch density indicators remain largely similar and highly significant for SVB returns and uninsured deposit outflows. For returns around the First Republic Bank collapse and insured deposit outflows, the coefficients are broadly comparable, though in one specification they lose statistical significance.

[10] Trading volume for the S&P 500 Banks index rose from 156 million on March 8 to 590 million on March 10, reaching a peak of 986 million on March 13. On March 14, volume declined, and prices rebounded from the March 13 close, though volume remained elevated in the following days. First Republic Bank was closed on Monday, May 1, so we focus on returns between Friday, April 28, and Tuesday, May 2; however, S&P 500 Banks trading volume peaked on May 3 and 4.

and significance of the coefficients remain similar with an extended window of March 6 through March 15 or for a time window beginning on March 1. With a narrower window, March 10 through March 13, we obtain significant coefficients with smaller magnitudes, which is natural given that prices moved less during that smaller window. For the collapse of First Republic Bank, coefficients are similar in magnitude but are imprecisely estimated for the two lowest density bins for the shorter alternative window of May 1 through May 4, while for a longer window, April 28 through May 4, we continue to find significantly lower returns for low-density banks.

Table AV in Appendix A also shows that the results on deposit outflows are robust to the inclusion of additional controls. Since some of those controls are available only for public banks, we present regressions in the sample of all banks and in the sample of public banks. Low density significantly increases the likelihood of large outflow of uninsured deposits. For insured deposits in the sample of public banks, the coefficient on the indicator for density below 2.5 is not statistically significant but remains positive and substantial in magnitude.

We examine brokered deposits as an alternative explanation in Appendix B. Although low-density banks hold a higher share of brokered deposits, these deposits are contractually locked and thus more stable than core deposits during a crisis. The instability of low-density banks is driven by their nonbrokered deposit base.

We study branch density in other time periods in Appendix C. We show that throughout 2000-2020 low branch density was associated with worse stock returns on days when banking sector did poorly, and better performance on days when banking sector did well, which is consistent with higher risk of low-density banks over the last two decades. Furthermore, the deposit rates offered by low-density banks were higher not only after the 2023 turmoil, but also in years preceding it.

The evidence on stock returns and deposit outflows confirms that the concentration of sophisticated depositors at low-density banks translated into measurable fragility during the 2023 banking crisis. Banks with the lowest branch density experienced stock returns over 11 percentage points lower than high-density banks and were 13–16 percentage points more likely to suffer large deposit outflows. These effects are robust to controlling for mark-to-market losses, suggesting that depositor composition—not just asset-side vulnerabilities—drove the differential performance. Branch density thus provides a new proxy for depositor sophistication that goes beyond regulatory categories such as insured versus uninsured status.

VI. Conclusion

Banks with low branch density experienced concentrated fragility during the 2023 regional banking crisis. We document that these banks attract financially and technologically sophisticated depositors who are more attentive to financial conditions and quicker to withdraw when concerned. These depositors also read more financial news, use real estate platforms such as Zillow, and drive electric vehicles—behaviors their bank's mobile app cannot cause—suggesting that selection into low-density banks, not just the technology these banks provide, shapes the behavior of their depositor base.

This distinction carries implications for how we think about digitization and financial stability. On one hand, rapid deposit growth at individual low-density banks warrants particular scrutiny because such growth concentrates flight-prone depositors at specific institutions. On the other hand, rising digitization across the banking sector as a whole need not increase aggregate fragility: as digital banking becomes standard rather than differentiating, the sorting of sophisticated depositors into a narrow set of banks should diminish.

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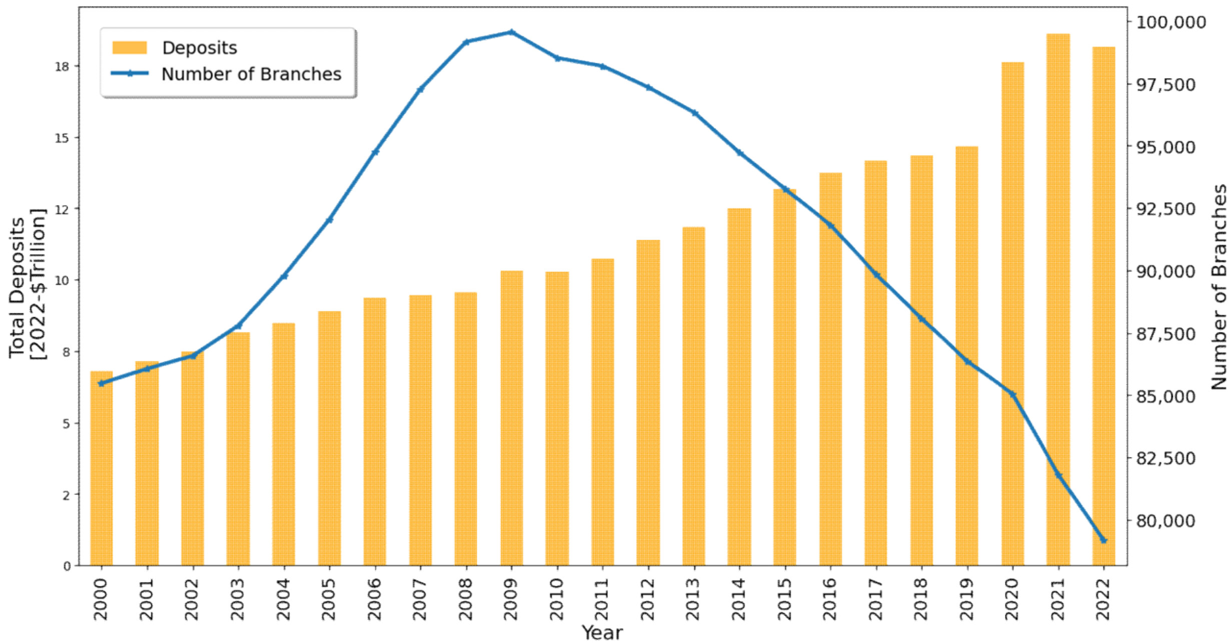
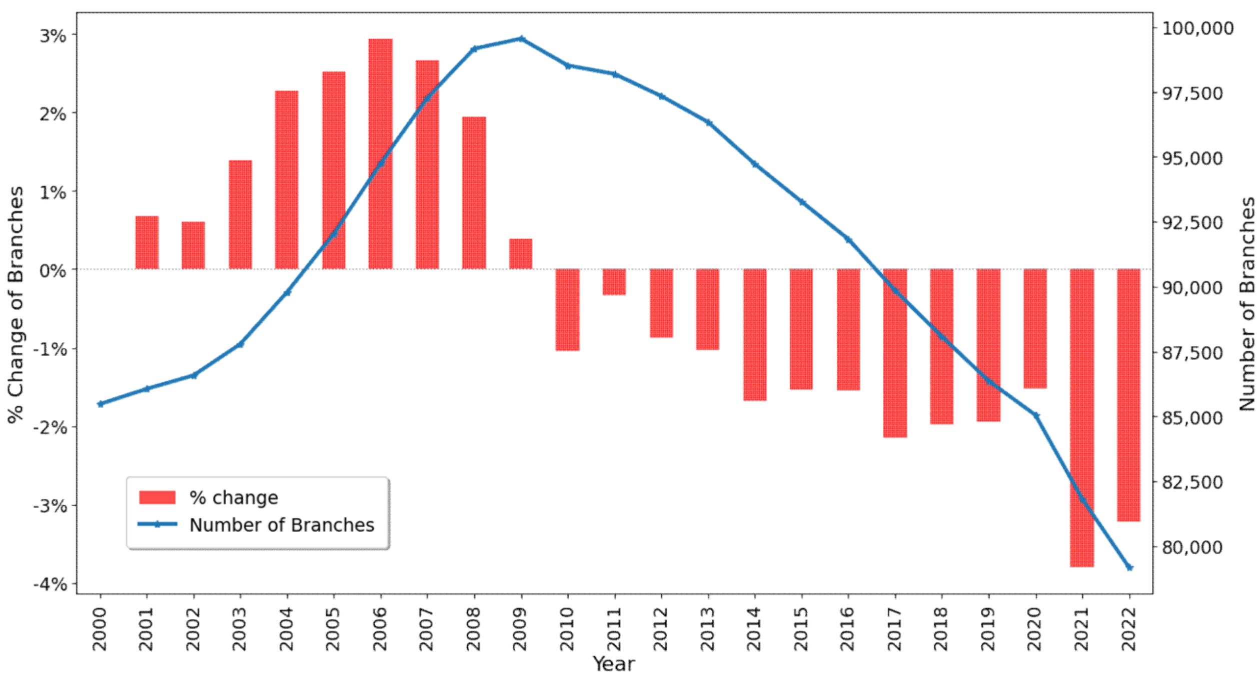


Panel A. Bank branches and total deposits in the United States



Panel B. Evolution of bank branches over time

Figure 1. Branches and deposits. This figure presents the aggregate trends in deposits and bank branches in the United States from 2000 to 2022. Panel A illustrates the growth of total deposits (left axis) over the entire period, while the number of bank branches (right axis) has been declining since 2010. Deposit amounts are adjusted for inflation and reported in 2022 dollars. Panel B shows the evolution of bank branches during the same period. The line represents the total number of bank branches (right axis), and the bars indicate the annual percentage change in branch counts (left axis). The sample includes all FDIC-insured banks. Source: Summary of Deposits.

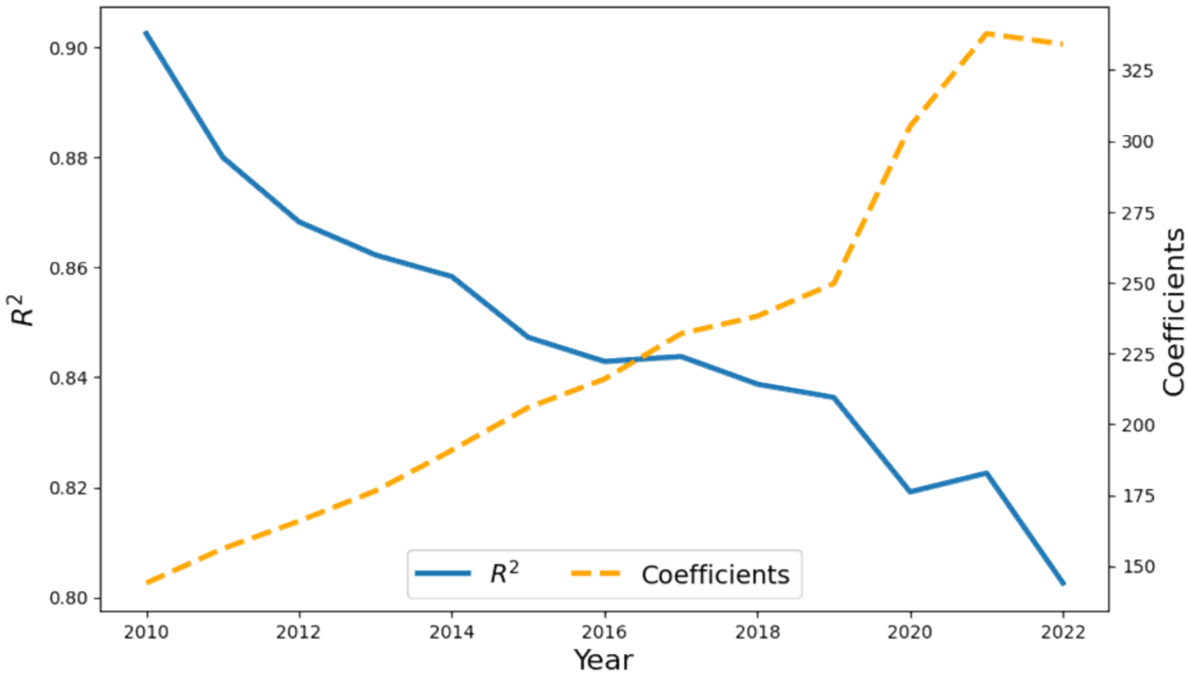


Figure 2. The explanatory power of bank branches for deposits. This figure illustrates the declining importance of bank branches in deposit-taking activities. It plots the coefficients (right axis) and R^2 values (left axis) from equation (1) over the period 2010 to 2022. Deposit amounts are reported in millions of 2022 real dollars. The sample includes all FDIC-insured banks. Source: Summary of Deposits.

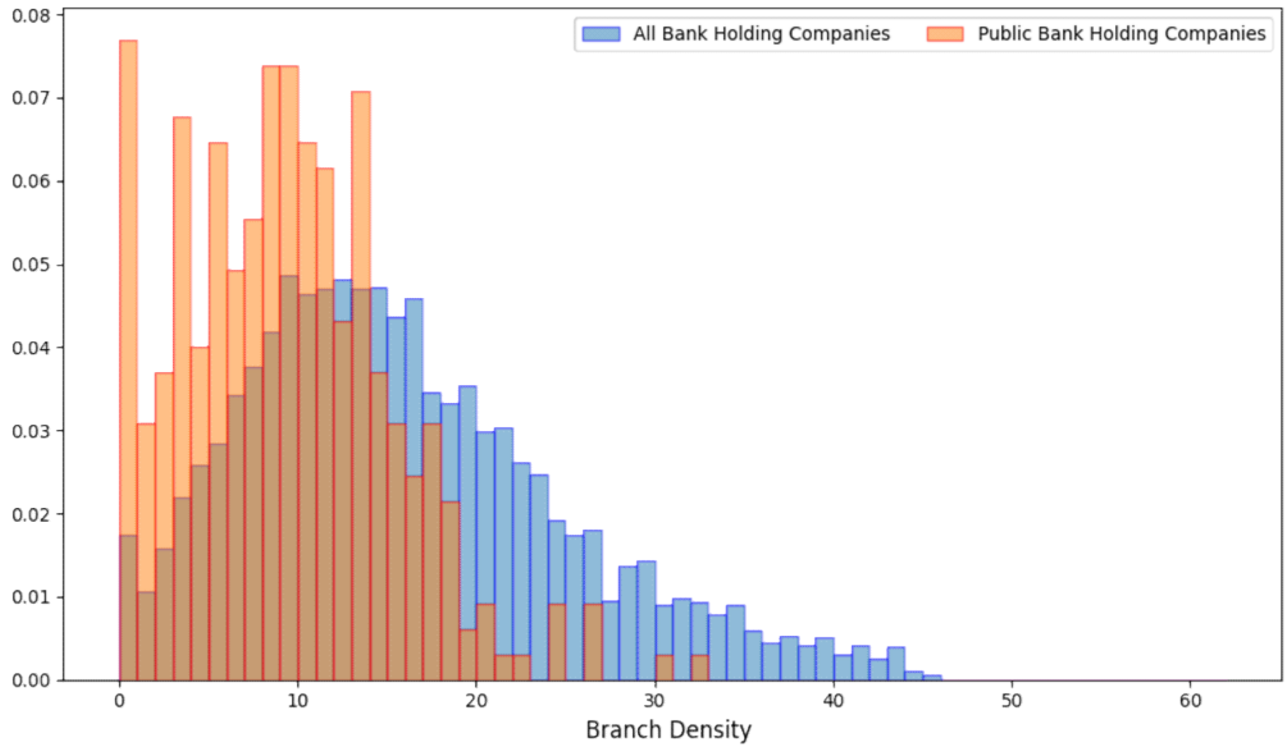


Figure 3. Distribution of Branch Density. This figure compares the distribution of branch density, measured as of June 2022, across two samples: all FDIC-insured bank holding companies (blue bars) and the subset of publicly traded bank holding companies (orange bars). Branch density is defined as the number of branches per $1 billion in deposits. To reduce the influence of extreme outliers, institutions with branch density above the 99th percentile (greater than 62) are excluded from the analysis. Source: Summary of Deposits.

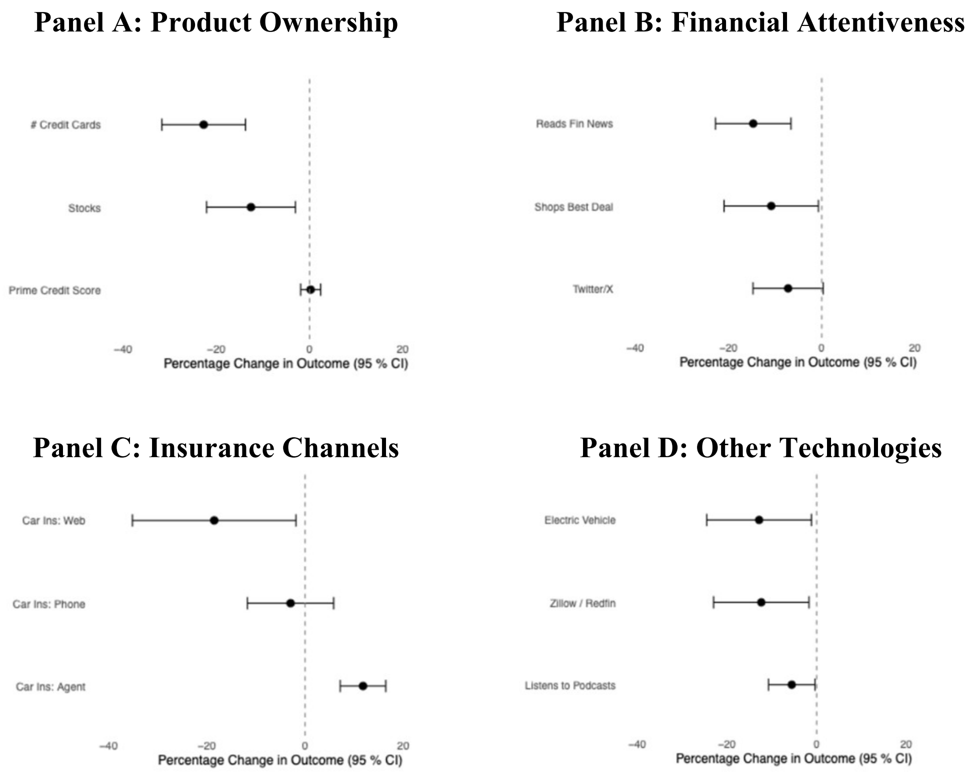


Figure 4. Branch Density and Financial Sophistication. The figure summarizes the predictive power of low branch density for different measures of financial and technological sophistication. Each dot is the coefficient β from specification (4) multiplied by the standard deviation of branch density among public banks, divided by the sample mean of each dependent variable to enable comparisons. Regressions control for demographics and three-digit zip code fixed effects.

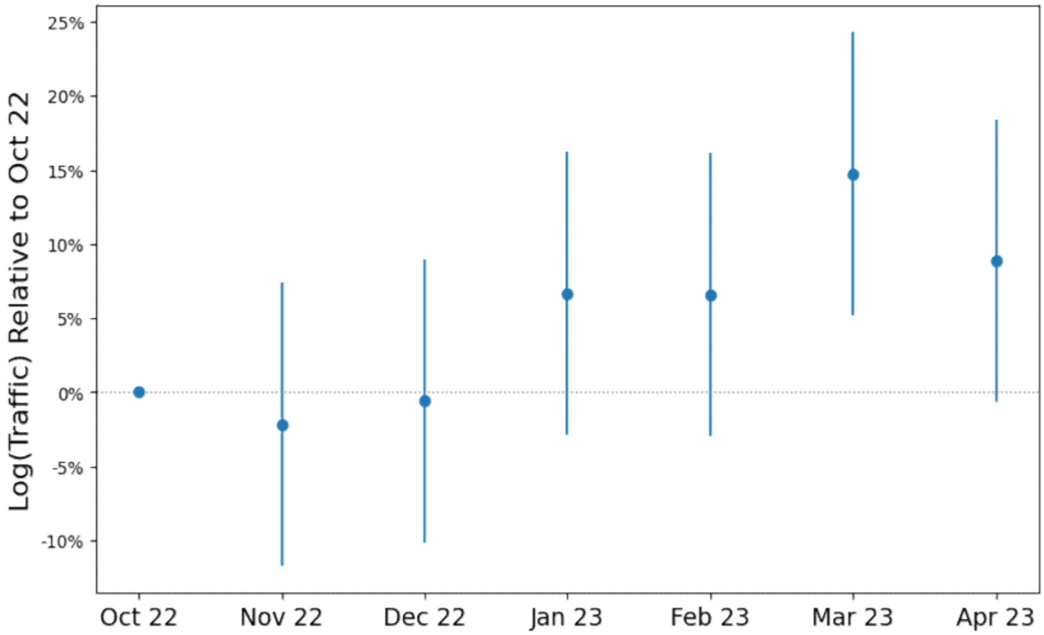
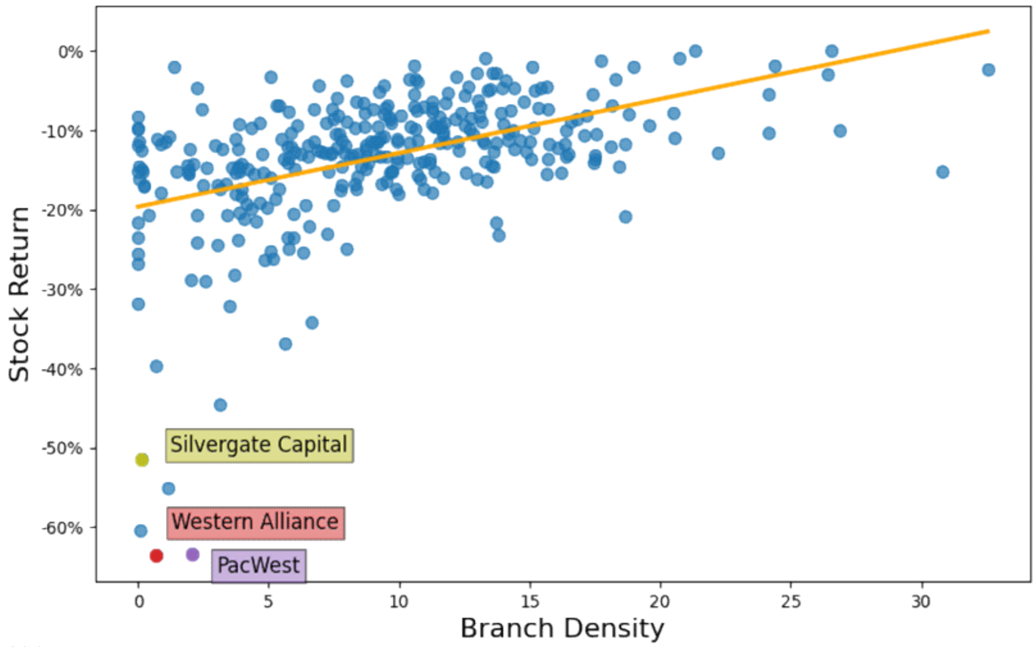
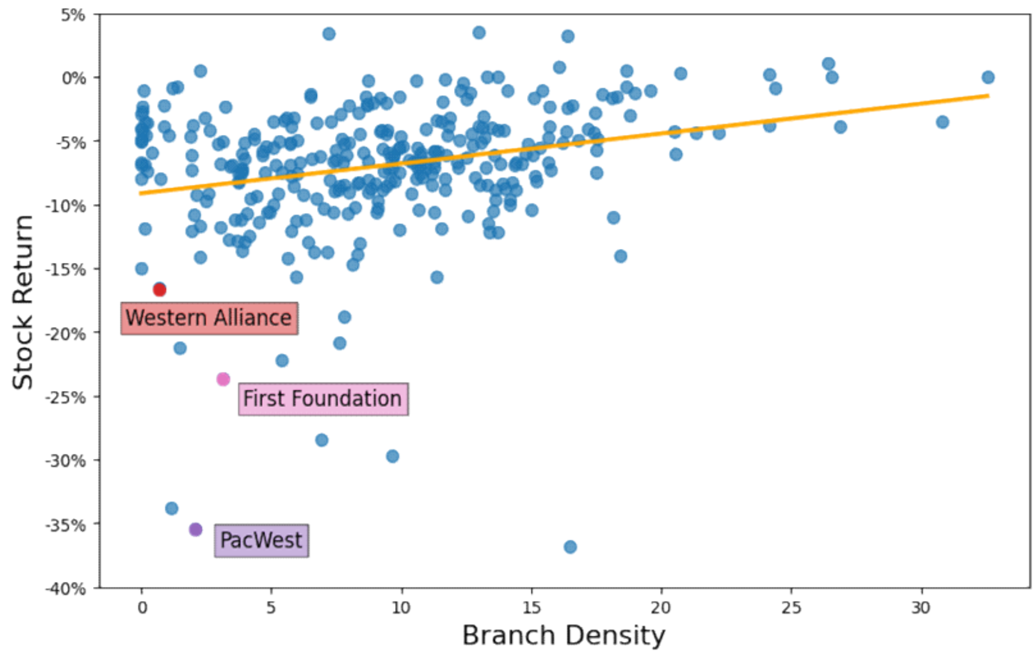


Figure 5. Website Traffic. This figure displays the volume of website traffic to our sample banks relative to the level in October 2022. Using October 2022 as the baseline (omitted category), we regress the natural logarithm of the number of web page visits on binary indicators for each month between November 2022 and April 2023, with bank fixed effects. The plotted value for October 2022 is normalized to zero by construction; bars for subsequent months represent 95% confidence intervals around the estimated coefficients.



Panel A. Silicon Valley Bank collapse



Panel B. First Republic Bank collapse

Figure 6. Branch density and stock return during the 2023 distress. This figure illustrates the relation between branch density and stock returns during two bank distress events in 2023: the collapse of Silicon Valley Bank (Panel A) and the failure of First Republic Bank (Panel B). Branch density is defined as the number of branches per $1 billion in deposits, measured as of June 2022. Stock returns are computed as the change in stock price from March 8 to March 13 for Panel A, and from April 28 to May 2 for Panel B. The sample consists of publicly traded bank holding companies. Banks that experienced particularly sharp declines in stock prices are labeled for reference.

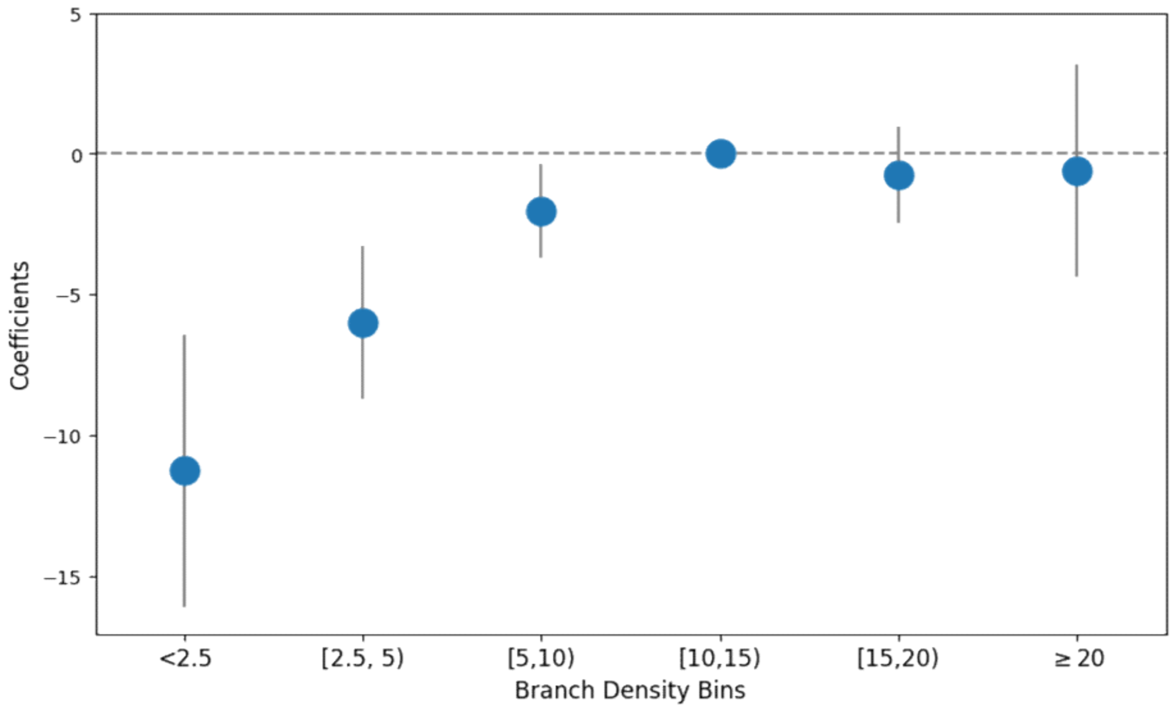


Figure 7. Nonlinearity: Branch Density and Stock Returns. This figure illustrates the nonlinear relationship between branch density and stock performance during the collapse of Silicon Valley Bank (SVB). Stock returns are measured as the change in stock price from March 8 to March 13, 2023. Branch density is defined as the number of branches per $1 billion in deposits, calculated at the bank holding company level using June 2022 data. Banks are grouped into six categories according to their branch density: <2.5, [2.5, 5), [5, 10), [10, 15), [15, 20), and ≥20. To capture potential nonlinearity, we estimate equation (2) using indicator variables for each branch density bin instead of a continuous branch density measure. The figure plots the estimated coefficients for each bin along with their 95% confidence intervals.

Table I
Summary Statistics

Notes: This table reports summary statistics for variables defined at the bank holding company (BHC) level. Branch density is measured as the number of branches per $1 billion in total deposits as of June 2022. Stock returns are calculated around the Silicon Valley Bank (SVB) (March 8–13, 2023) and First Republic Bank (April 28–May 2, 2023) failures. Changes in total, insured, and uninsured deposits refer to the difference between Q4 2022 and Q1 2023. Insured Deposits/Total Deposits, Deposits/Assets, log(Assets), and corporate deposit share are measured at year-end 2022. Deposit growth over Covid 19 is defined from 2019 to 2022. MTM losses follow Jiang et al. (2024). Deposit rates for 12-month and 24-month CDs are based on 2022 RateWatch data. IT Growth reflects growth in IT budgets from 2010 to 2017 using Aberdeen data. Online Traffic measures the change in website visits from February to March 2023 using Semrush, with an alternative scaled by total deposits. Customer-Facing and Technical Skills Demand in 2022 are derived from a structural topic model using Lightcast data. Local demographic variables from the American Community Survey are aggregated to the BHC level using branch-weighted averages. Demographic variables from the MRI-Simmons survey are at the individual level. See Appendix A for details.

Variable Name	*N*	Mean	Std	10%	25%	50%	75%
A. Bank Characteristics							
Branch Density	3,609	19.406	12.212	5.455	9.480	14.854	21.946
Branch Density (Public Banks)	324	9.259	5.880	1.926	4.841	9.074	13.041
Stock Return (SVB)	327	-13.340	8.630	-21.645	-15.404	-12.067	-8.537
Stock Return (First Republic)	325	-6.932	5.248	-12.032	-8.817	-6.295	-3.986
Dep Change Q422-Q123	3,536	0.771	8.289	-5.218	-2.600	0.241	3.312
Uninsured Dep Change Q422-Q123	3,535	-2.712	17.238	-15.519	-9.643	-3.750	2.474
Insured Dep Change Q422-Q123	3,535	5.512	29.716	-1.843	0.215	2.431	5.895
Insured Dep/Total Dep	3,608	0.572	0.141	0.390	0.493	0.587	0.668
Dep/Assets	3,608	0.861	0.075	0.780	0.832	0.875	0.906
Dep Growth 2019-2022	3,437	0.481	1.303	0.155	0.259	0.373	0.533
Log(Assets)	3,609	13.074	1.514	11.405	12.076	12.857	13.783
MTM Losses	3,608	0.136	0.045	0.080	0.106	0.134	0.164
Corporate Dep/Total Dep	690	0.379	0.175	0.159	0.257	0.361	0.471
Average Deposit	3,607	6971	288503	1368	1559	1790	2055
Deposit Rate 12MCD10K	3,200	1.867	1.306	0.248	0.742	1.688	2.851
Deposit Rate 24MCD100K	3,133	1.828	1.157	0.300	0.794	1.767	2.688
Deposit Rate (Call Reports)	3,593	0.243	0.155	0.079	0.138	0.217	0.314
B. Technology							
IT Growth 2010-17	700	2.876	0.854	1.904	2.383	2.856	3.352
Web Traffic Mar/Feb 23	182	1.275	1.085	0.515	0.789	1.040	1.364
Web Traffic/Deposits	185	0.041	0.088	0.003	0.010	0.021	0.038
Customer-Facing Skills Demand	274	0.260	0.109	0.101	0.189	0.260	0.336
Technology Skills Demand	274	0.075	0.084	0.011	0.026	0.047	0.092
Back Office Skills	274	0.214	0.082	0.124	0.156	0.202	0.253
Management Skills	274	0.192	0.046	0.139	0.160	0.189	0.220
General Skills	274	0.125	0.028	0.093	0.106	0.123	0.141
C. Demographics (ACS)							
Urban	3,607	39.710	43.007	0.000	0.000	18.107	96.226
Log(CountyIncome)	3,607	10.755	0.219	10.487	10.623	10.744	10.885
Aged 60+	3,607	19.941	4.008	15.172	17.235	19.600	22.262
Higher Education	3,607	22.977	9.03	13.3	16.26	20.753	28.29

(continued on the next page)

Table I
Summary Statistics *(continued)*

Variable Name	*N*	Mean	Std	10%	25%	50%	75%
D. Demographics (MRI)							
Urban	63,252	0.90	0.3	1	1	1	1
Log Household Income	63,252	11.21	0.88	10.11	10.71	11.37	11.83
Aged 60+	63,252	0.25	0.43	0	0	0	1
Higher Education	63,252	0.40	0.49	0	0	0	1
Payment app used	63,252	0.44	0.5	0	0	0	1
Banking app used	63,252	0.77	0.42	0	1	1	1
Values branch location	63,252	0.52	0.5	0	0	1	1
Values interest rates	63,252	0.40	0.49	0	0	0	1
Shops best deal	63,252	0.19	0.39	0	0	0	0
Likely to change banks	63,252	0.07	0.26	0	0	0	0
# Credit cards	63,252	1.78	1.49	0	1	1	2
Money market funds	63,252	0.10	0.3	0	0	0	0
Stocks	63,252	0.28	0.45	0	0	0	1
Prime Credit Score	63,237	0.80	0.4	0	1	1	1
Reads fin news	63,252	0.29	0.45	0	0	0	1
Twitter/X	63,252	0.18	0.38	0	0	0	0
Car ins: web	63,252	0.18	0.38	0	0	0	0
Car ins: phone	63,252	0.22	0.41	0	0	0	0
Car ins: agent	63,252	0.49	0.5	0	0	0	1
Redfin / Zillow	63,252	0.19	0.39	0	0	0	0
Electric vehicle	63,252	0.06	0.24	0	0	0	0
Listens to podcasts	63,252	0.27	0.44	0	0	0	1

Table II

Characteristics of Bank Customers by Branch Density

Notes: Panel A uses data from bank call reports. Branch density is defined as the number of branches per $1 billion in deposits as of June 2022 and is categorized into discrete bins. We include indicator variables for each bin, with branch density greater than or equal to 10 serving as the omitted category. Columns (1) and (2) use as dependent variables the ratio of corporate deposits to total deposits and the logarithm of average deposit size per account, respectively. Corporate deposit data are available only for a subset of banks that meet specific reporting requirements. Columns (3)–(6) use bank-level weighted averages of county-level demographics, where county-level values are weighted by each bank's deposits in the county. All regressions in Panel A control for log(total assets), total asset quintile fixed effects, deposits-to-assets ratio, share of insured deposits, mark-to-market losses, and deposit growth from 2019 to 2022. Robust standard errors in parentheses. Panel B uses individual level data from MRI and shows the results of regressing individual demographics on the branch density of the consumer's bank. The % effect is computed from multiplying the coefficient by the standard deviation of branch density among public banks and dividing by the unconditional mean of the dependent variable. Standard errors are clustered at the bank level. See Appendix A for detailed variable definitions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A. Bank-Level Data and County-Level Proxies

	(1) Corp. Dep/Total	(2) Log(Avg Dep)	(3) Urban	(4) Log(County Income)	(5) Age 60+	(6) Higher Education
Branch Density < 2.5	0.139***	1.222***	26.59***	0.161***	-1.872***	8.895***
	(0.0387)	(0.157)	(3.195)	(0.0210)	(0.372)	(1.024)
Branch Density [2.5, 5)	0.0962***	0.497***	21.94***	0.111***	-1.207***	5.572***
	(0.0213)	(0.0665)	(3.084)	(0.0180)	(0.331)	(0.748)
Branch Density [5, 10)	0.0345***	0.204***	13.68***	0.0825***	-0.787***	3.445***
	(0.0131)	(0.0246)	(1.866)	(0.00969)	(0.181)	(0.390)
Dep/Assets	0.282**	-1.879***	-64.99***	-0.362***	1.643*	-20.73***
	(0.112)	(0.344)	(11.84)	(0.0476)	(0.929)	(2.020)
Insured Dep /Total Dep	-0.412***	-2.140***	-56.06***	-0.104***	5.468***	-7.717***
	(0.0734)	(0.194)	(5.695)	(0.0289)	(0.568)	(1.153)
MTM Losses	-0.326*	-1.061***	-17.51	0.0828	2.838*	-3.867
	(0.182)	(0.264)	(15.67)	(0.0808)	(1.559)	(3.357)
Dep Growth 2019-2022	0.0368***	0.0271	0.484	0.00242*	0.00396	0.351***
	(0.00972)	(0.0166)	(0.336)	(0.00126)	(0.0295)	(0.0515)
N	662	3,437	3,436	3,436	3,436	3,436
R^2	0.285	0.505	0.313	0.167	0.162	0.291
Size Control	X	X	X	X	X	X

Panel B. Individual Depositor Data

	(1) Log(HH Income)	(2) Age 60+	(3) Higher Education
Branch Density	-0.02**	0.98**	-0.53+
	(0.01)	(0.27)	(0.26)
N	63,252	63,252	63,252
Zip-3 FE	X	X	X
% Effect of 1 SD Increase	-10	19	-7

Table III

Rate Sensitivity, Financial Technology, and Branch Density

Notes: This table uses individual level data from the MRI-Simmons survey to study how measures of interest rate sensitivity and financial technology adoption vary across banks with different branch density. Dependent variables are scaled by 100 so that coefficients can be interpreted as percentage point effects. The dependent variables are indicators for whether the consumer reports interest rates as an important factor when choosing a bank (column (1)), invests in a money market mutual fund (column (2)), expects to switch banks in the next 12 months (column (3)), reports branch location as an important factor when choosing a bank (column (4)), has used a mobile banking app in the past 12 months (column (5)), and has used Zelle, Venmo, or Cash App in the past 30 days (column (6)). Branch density is defined as the number of branches per $1 billion of deposits for each consumer's bank. The % effect is computed from multiplying the coefficient by the standard deviation of branch density among public banks and dividing by the unconditional mean of the dependent variable. Standard errors are clustered at the bank level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Interest Rate Sensitivity			Financial Technologies		
	(1)	(2)	(3)	(4)	(5)	(6)
	Values Interest	Money Market	Likely Change Banks	Values Location	Banking App	Payment App
Branch Density	-1.54**	-0.27*	-0.43**	1.51***	-1.37***	-1.53***
	(0.56)	(0.13)	(0.14)	(0.41)	(0.24)	(0.27)
Log Income	3.50***	4.18***	-0.37	2.28***	5.60***	5.65***
	(0.60)	(0.27)	(0.27)	(0.37)	(0.26)	(0.44)
Age 60+	-6.29***	10.78***	-1.61***	11.42***	-21.22***	-27.23***
	(0.83)	(0.49)	(0.31)	(0.52)	(1.65)	(0.54)
Higher Education	1.82**	2.88***	0.27	0.43	2.29***	4.53***
	(0.63)	(0.43)	(0.42)	(0.94)	(0.26)	(0.60)
N	63,252	63,252	63,252	63,252	63,252	63,252
Zip-3 FE	X	X	X	X	X	X
% effect of 1 SD Increase	-19	-14	-30	15	-9	-17

Table IV

Rate Sensitivity, Financial Technology, and Local Branch Presence

Notes: This table uses individual level data from the MRI-Simmons survey to study how measures of interest rate sensitivity and financial technology adoption vary within banks as a function of the local branch presence. The number of local branches is the number of branches that a consumer's bank has in the consumer's three-digit zip code. It is normalized by the within zip code standard deviation of the number of branches across banks so that the coefficient can be interpreted as the effect of a one standard deviation increase in branch presence. Columns (1)-(3) report the results for three measures of rate sensitivity: an indicator for whether the consumer reports that interest rates are an important factor when choosing a bank, whether the consumer invests in money market funds, and whether they are likely to change banks in the next 12 months. Columns (4)-(6) report the results for three measures of technology adoption: indicators for whether the consumer reports that branch location is an important factor in choosing a bank, whether the consumer has used a bank mobile app in the past 12 months, and whether the consumer has used a fast-payment app such as Zelle, Venmo, or Cash App in the past 30 days. The % effect is computed from dividing the coefficient by the unconditional mean of the dependent variable. Dependent variables are scaled by 100 so that coefficients can be interpreted as percentage point effects. Standard errors are clustered at the bank-zip-3 level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Interest Rate Sensitivity			Financial Technologies		
	(1)	(2)	(3)	(4)	(5)	(6)
	Values Interest	Money Market	Likely Change Banks	Values Location	Banking App	Payment App
Local Branches (SD)	-1.17***	-0.46*	-0.98***	-0.26	-1.00***	-0.89*
	(0.41)	(0.27)	(0.22)	(0.39)	(0.37)	(0.47)
Log Income	3.14***	4.02***	-0.32	2.04***	5.63***	5.65***
	(0.39)	(0.24)	(0.21)	(0.43)	(0.37)	(0.41)
Age 60+	-5.99***	10.43***	-1.50***	11.49***	-20.93***	-26.84***
	(0.76)	(0.54)	(0.40)	(0.83)	(0.78)	(0.72)
Higher Education	1.58**	2.82***	0.10	0.21	2.26***	4.50***
	(0.65)	(0.42)	(0.33)	(0.66)	(0.55)	(0.64)
N	54,296	54,296	54,296	54,296	54,296	54,296
Zip-3 FE	X	X	X	X	X	X
Bank FE	X	X	X	X	X	X
% effect of 1 SD Increase	-3	-5	-14	-1	-1	-2

Table V
Branch Density and Technology

Notes: Branch density is defined as the number of branches per $1 billion in deposits as of June 2022 and is grouped into discrete bins. The regression includes indicator variables for each bin, with branch density ≥10 as the omitted category. IT Growth reflects the change in IT budgets from 2010 to 2017. Web Traffic is measured either as the ratio of online traffic in March 2023 to February 2023 (column (2), Panel A), or as March 2023 traffic scaled by total deposits. Outcome variables in Panel B capture labor skill demand in 2022, with each skill type scaled by the total number of job postings that year. All regressions control for log(total assets), total asset quintile fixed effects, deposits-to-assets ratio, share of insured deposits, and mark-to-market (MTM) losses. See Appendix A for detailed variable definitions. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A	(1) IT Growth 2010-2017	(2) Web Traffic Mar/Feb 23	(3) Web Traffic /Total Dep
Branch Density < 2.5	0.383*	0.727**	0.0510*
	(0.202)	(0.297)	(0.0285)
Branch Density [2.5, 5)	0.297**	0.311	0.00419
	(0.137)	(0.253)	(0.0145)
Branch Density [5, 10)	0.00981	0.255	-0.00682
	(0.0728)	(0.219)	(0.00930)
Log(Assets)	0.0783***	-0.162*	0.0110**
	(0.0290)	(0.0912)	(0.00500)
Dep/Assets	-0.824*	0.687	-0.0466
	(0.439)	(1.108)	(0.0943)
Insured Dep	0.142	-0.0807	0.212***
/Total Dep	(0.295)	(0.607)	(0.0725)
MTM Losses	0.0716	-4.633	-0.328*
	(0.837)	(2.931)	(0.175)
Dep Growth	0.233***	0.432	-0.0316**
2019-2022	(0.0884)	(0.301)	(0.0148)
N	697	180	184
R^2	0.114	0.128	0.286
Size Control	X	X	X

(Panel B on next page)

Panel B	(1)	(2)	(3)	(4)	(5)
			Labor Skill Demand		
	Technology	Customer-facing	Management	Back Office	General
Branch Density	0.106***	-0.160***	0.0518***	0.0000676	0.00223
< 2.5	(0.0180)	(0.0184)	(0.00923)	(0.0165)	(0.00532)
Branch Density	0.0335***	-0.0740***	0.0266***	-0.00280	-0.000883
[2.5, 5)	(0.0112)	(0.0155)	(0.00684)	(0.0159)	(0.00530)
Branch Density	0.0139**	-0.0128	0.0137**	-0.0255*	0.00120
[5, 10)	(0.00573)	(0.0134)	(0.00616)	(0.0130)	(0.00457)
Log(Assets)	0.0208***	-0.000198	0.00208	-0.0131***	-0.00542***
	(0.00462)	(0.00449)	(0.00205)	(0.00409)	(0.00144)
Dep/Assets	0.0411	0.0719	-0.0438*	-0.0838	-0.0235
	(0.0668)	(0.0500)	(0.0262)	(0.0570)	(0.0168)
Insured Dep	0.0622	0.0323	0.0205	-0.0714**	-0.000315
/Total Dep	(0.0415)	(0.0323)	(0.0179)	(0.0322)	(0.0117)
MTM Losses	-0.208*	0.347***	-0.113*	-0.0880	0.0198
	(0.111)	(0.131)	(0.0630)	(0.110)	(0.0406)
Dep Growth	-0.0150*	-0.00811	-0.00561	0.0187**	0.00762
2019-2022	(0.00897)	(0.0102)	(0.00523)	(0.00939)	(0.00594)
N	270	270	270	270	270
R^2	0.462	0.432	0.273	0.126	0.114
Size Control	X	X	X	X	X

Table VI
Branch Density and Deposit Rates

Notes: Branch density is defined as the number of branches per $1 billion in deposits as of June 2022 and is categorized into discrete bins. The regression includes indicator variables for each bin, with branch density ≥10 as the omitted category. Deposit Rate 12MCD10K is the average annual percentage yield (APY) on 12-month CDs with a $10,000 minimum deposit, and 24MCD100K is the corresponding measure for 24-month CDs with a $100,000 minimum, both at the bank holding company level in 2022. Average Deposit Rate is calculated as interest expenses on domestic deposits divided by the value of domestic deposits, based on call reports. All regressions control for log(total assets), total asset quintile fixed effects, deposits-to-assets ratio, share of insured deposits, and mark-to-market losses. See Appendix A for detailed variable definitions. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)
		Deposit Rate	
	12MCD10K	24MCD100K	Average Deposit Rate
Branch Density < 2.5	0.417***	0.476***	0.228***
	(0.0689)	(0.0734)	(0.0295)
Branch Density [2.5, 5)	0.179***	0.229***	0.104***
	(0.0381)	(0.0448)	(0.0137)
Branch Density [5, 10)	0.0787***	0.0867***	0.0490***
	(0.0174)	(0.0196)	(0.00634)
Log(Assets)	-0.0514***	-0.0746***	-0.00284
	(0.0135)	(0.0142)	(0.00480)
Dep/Assets	-0.662***	-0.819***	-0.534***
	(0.115)	(0.131)	(0.0740)
Insured Dep/Total Dep	0.0320	0.0649	-0.00904
	(0.0654)	(0.0705)	(0.0291)
MTM Losses	-1.048***	-1.095***	-0.182***
	(0.156)	(0.174)	(0.0573)
Dep Growth 2019-2022	0.0480***	0.0545***	0.00900
	(0.0153)	(0.0167)	(0.00559)
N	3,103	3,024	3,369
R^2	0.101	0.110	0.275
Size Controls	X	X	X

Table VII
Branch Density and Stock Prices During the 2023 Banking Crisis

Notes: The sample consists of publicly traded bank holding companies. The stock return around the Silicon Valley Bank (SVB) collapse is measured as the relative change in the average closing price from March 8 to March 13, 2023; the return around the First Republic Bank collapse is calculated from April 28 to May 2, 2023. Branch density is defined as the number of branches per $1 billion in deposits as of June 2022. Branch density is also categorized into bins, and indicator variables are used for each bin. The omitted category is branch density greater than or equal to 10. Deposits-to-assets ratio and the share of FDIC-insured deposits are measured at year-end 2022. mark-to-market (MTM) losses are expressed as a percentage of assets in Q1 2022, following Jiang et al. (2024). Dep Growth 2019–2022 refers to the growth in total deposits from the end of 2019 to the end of 2022. All regressions control for the logarithm of total assets and include fixed effects for total asset quintiles (in five groups). Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)
	Stock Return (SVB)			Stock Return (First Republic)	
Branch Density	0.553***	0.474***		0.203***	
	(0.104)	(0.0987)		(0.0536)	
Branch Density < 2.5			-11.11***		-2.835**
			(2.439)		(1.427)
Branch Density [2.5, 5)			-5.811***		-1.907**
			(1.374)		(0.740)
Branch Density [5, 10)			-1.815**		-1.475**
			(0.817)		(0.638)
Dep/Assets		-13.00**	-20.82***	-4.730	-5.418
		(5.841)	(6.754)	(3.133)	(3.689)
Insured Dep/Total Dep		8.374**	8.691**	3.626	4.142*
		(4.203)	(4.307)	(2.270)	(2.485)
MTM Losses		-9.712	-13.17	-29.40**	-28.59**
		(11.47)	(12.07)	(12.11)	(12.46)
Dep Growth 2019-2022		-2.553**	-2.728**	0.175	0.126
		(1.246)	(1.233)	(0.449)	(0.473)
N	324	314	314	312	312
R^2	0.236	0.293	0.350	0.191	0.186
Size Control	X	X	X	X	X

Table VIII
Branch Density and Deposit Outflows in Q1 2023

Notes: Branch density is defined as the number of branches per $1 billion in deposits as of June 2022 and is categorized into discrete bins. The regression includes indicator variables for each bin, with branch density greater than or equal to 10 serving as the omitted category. Dependent variables are indicators for large net deposit outflows—uninsured (columns (1) and (3)) or insured (columns (2) and (4))—from Q4 2022 to Q1 2023. These indicators equal 100 for banks below the 10th percentile (columns (1) and (2)) or 25th percentile (columns (3) and (4)) of the corresponding deposit change distribution, and 0 otherwise. All regressions control for log(total assets), total asset quintile fixed effects, deposits-to-assets ratio, share of insured deposits, mark-to-market (MTM) losses, and deposit growth from 2019 to 2022. See Appendix A for detailed variable definitions. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)
	Top Decile Outflow Indicator		Top Quartile Outflow Indicator	
	Uninsured	Insured	Uninsured	Insured
Branch Density < 2.5	13.10***	13.20***	16.35***	14.21***
	(4.096)	(3.836)	(5.136)	(4.512)
Branch Density [2.5, 5)	1.990	1.357	9.899**	1.737
	(2.441)	(2.068)	(3.869)	(3.072)
Branch Density [5, 10)	-0.0450	2.401*	0.983	2.361
	(1.376)	(1.370)	(2.066)	(1.964)
Dep/Assets	3.953	-3.631	30.35**	17.10
	(9.908)	(8.721)	(13.02)	(11.41)
Insured Dep	-6.369	2.601	-7.529	16.72***
/Total Dep	(5.014)	(4.955)	(6.794)	(6.448)
MTM Losses	-12.59	-24.10*	-15.78	-43.94**
	(12.25)	(13.19)	(17.72)	(17.76)
Dep Growth	4.360***	-2.031	2.975	-6.351***
2019-2022	(1.662)	(1.523)	(2.105)	(1.927)
N	3,367	3,367	3,367	3,367
R^2	0.018	0.036	0.012	0.063
Size Control	X	X	X	X

Internet Appendix for Bank Branch Density and Fragility

EFRAIM BENMELECH, LULU WANG, JUN YANG, and MICHAŁ ZATOR

Appendix A. Details of Data Creation Process

A.1. Variable Definitions and Constructions

Variable	Descriptions
CRSP Variables	
Stock Return (SVB Failure)	Relative change of the close price from March 8, 2023, to March 13, 2023.
Stock Return (First Republic Failure)	The change in the close price between April 28, 2023, and May 2, 2023.
Summary of Deposits Variables	
Branch Density	We use deposit-taking branches identified by the following branch service type ("brsertyp"): 11 (full-service brick-and-mortar office: accept deposits, make loans, open/close accounts, loan officer on site, normal hours, full-time staff; may have safe deposit facilities on site), 12 (full-service retail office: accept deposits, make loans, open/close accounts, loan officer on site, normal hours, full-time staff, located in a retail facility such as a supermarket or department store), 23 (limited-service facility office: accept deposits and payments but may, however, not offer other services; may be a bank's own facility, located within a retail establishment or drive-through branch), 29 (limited-service mobile office: accept deposits, accept payments and withdrawals, and may be located in a nursing home, etc.) These deposit-taking branches account for over 99% of all branch types. Branch density at the BHC-year level is defined as all deposit-taking branches scaled by deposits from all branch types aggregated to the BHC level. In the cross-sectional analysis, branch density is calculated using data as of June 2022.
ΔBranch Density	Branch density in June 2022 minus branch density measured in June 2010.
Branch Density 2010	Branch density as of June 2010.
Call Report Variables	
Dep Change Q4 2022–Q1 2023	Percentage change of total domestic deposits (RCON2200) in Q1 2023 relative to total domestic deposits in Q4 2022. Bank-level data are aggregated at the BHC level.
Insured Dep Change Q4 2022–Q1 2023	Percentage change of insured deposits in Q1 2023 relative to insured deposits in Q4 2022. We follow Acharya and Mora (2015) and define insured deposits as the sum of RCONF049 and RCONF045 in the bank-level call reports. Bank-level data are then aggregated at the BHC level.
Insured Dep/Total Dep	The fraction of insured deposits (RCONF049 + RCONF045) out of total domestic deposits (RCON2200). Bank-level data are aggregated at the BHC level.

Uninsured Dep Change Q4 2022–Q1 2023	Percentage change of uninsured deposits in Q1 2023 relative to uninsured deposits in Q4 2022. Uninsured deposits are calculated by subtracting insured deposits from total domestic deposits. Bank-level data are aggregated at the BHC level.
Log(Assets)	Natural logarithm of total assets. Total assets are obtained from CRSP for publicly traded banks or aggregated total assets (RCON2170) from call reports for other banks.
Dep Growth 2019–2022	Growth rate in total domestic deposits from the end of 2019 to the end of 2022. Bank-level data are aggregated at the BHC level.
Dep/Assets	Total domestic deposits (RCON2200) scaled by total assets.
Corporate Dep/Total Dep	Transaction accounts total (RCONB549)—total deposits in those noninterest-bearing and interest-bearing transaction account deposit products intended primarily for individuals for personal, household, or family use (RCONP753 + RCONP754) + components of nontransaction account deposit products that are *not* intended primarily for individuals for personal, household, or family use (RCONP757 + RCONP759). Corporate deposits are scaled by total deposits in domestic offices. Note: Starting from 2019, items 6 and 7 in Schedule RC-E Part I are reported in December only by institutions with assets >=1$b and answering *yes* to item 5. The $1b size cutoff is based on total assets value as of different years and sometimes not specified (e.g., 2014 and 2015). We use the reported number in December call reports when both RCONB549 and the sum of RCONP753+RCONP754 are greater than zero.
Log(Avg Dep)	Logarithm of total domestic deposits (RCON2200) divided by number of accounts (RCONF050 + RCONF046 + RCONF052 + RCON048).
MTM Losses	Mark-to-market losses scaled by total assets measured in Q1 2022. Following Jiang et al. (2024), MTM losses are measured using call reports data on bank holdings of mortgages and treasuries, combined with changes in Treasury Bond prices and Mortgage-Backed Securities (MBS) Exchange Traded Funds (ETF). $MTM\ losses = \sum_m (RMBS_m + Mortgages_m) \times Multiplier \times \Delta TreasuryPrice_m + \sum_m Treasury\ and\ Other\ Securities\ and\ Loans \times \Delta TreasuryPrice_m$, where *m* represents the maturity and repricing breakdowns in call reports: three months or less, over three months through 12 months, over one year through three years, over three years through five years, over five years through 15 years, and over 15 years. *ΔTreasuryPrice_m* indicates the change in Treasury Bond prices for maturity *m* from Q1 2022 to Q1 2023 (see Figure 1c in Jiang et al. (2024)). Multiplier is the ratio of the change in the iShares MBS ETF over the change in the S&P Treasury Bond Index between 2022 and 2023. As in Cookson et al. (2026), this measure is aggregated to the BHC level. Finally, the negative of MTM losses is scaled by the total assets value in Q1 2022.
Deposit Rate -Call Report	Interest expenses on domestic deposits (RIAD4508 + RIAD0093 + RIADHK03 + RIADHK04) divided by total domestic deposits (RCON2200).

Brokered Dep/Total Dep	The fraction of brokered deposits (RCON2365) out of total deposits (RCON2200). Bank-level data are aggregated at the BHC level.
CRE Loans	The ratio of the value of commercial real estate loans to assets.
Non-performing Loans	The ratio of the value of nonperforming loans to assets.
MRI-Simmons Variables	
Age 60+	Indicator that the respondent is age 60 or older.
Urban	County in Nielsen size class A, B, or C (captures all metropolitan areas and a few micropolitan areas; around 80% of population).
Log Household Income	Log of the respondent's total household income.
Higher Education	The respondent has a bachelor's degree or higher.
Branch density	Branch density of the bank the household uses.
# Local Branches	Number of branches of the bank used by the household in the household's three-digit zip code.
# Cards	Number of credit cards the consumer has at different banks.
Owns Stock	Indicator that the consumer owns stocks.
Money Market	Indicator that the consumer owns a money market fund.
Prime Score	Indicator that the consumer has a FICO credit score of 660 or higher.
Reads Fin News	The respondent agrees somewhat or completely: "I regularly read financial news or financial publications."
Best Deal	The respondent agrees completely: "I always shop for the best deal when choosing financial/investment services."
Likely Change Banks	The respondent answers "very likely" or "somewhat likely" to "How likely are you to change banks in the next 12 months?"
Values Interest Rates	The respondent considers interest rates to be "very important" when choosing a bank.
Payment App	The respondent used Zelle, Cash App, or Venmo in the past 30 days.
Uses Twitter	The respondent visited or used Twitter/X in the previous 30 days.
Banking App	The respondent used a banking app in the past 12 months.
Values Location	The respondent considers branch location to be "very important" when choosing a bank.
Car Ins: Agent	The respondent acquired current auto insurance via an agent.
Car Ins: Web	The respondent acquired current auto insurance via a website.
Car Ins: Phone	The respondent acquired current auto insurance via phone.
Redfin / Zillow	Indicator for using Redfin, Trulia, or Zillow to research real estate in the past 12 months.
Electric Vehicle	Indicator for owning or leasing a hybrid or alternative-fuel vehicle.
Podcast User	Indicator for listening to any podcast in the past 7 days.
Other Variables	
IT Growth 2010–2017	Percentage change in IT budget from 2010 to 2017. We match establishment-level IT data from Aberdeen with branches in summary of deposits first and then aggregate data to the BHC level. The data is available for around 700 institutions.
Online Traffic Mar/Feb 23	The ratio of online traffic in March 2023 relative to the online traffic in February 2023. We manually collect individual website traffic analysis reports from Semrush for each publicly traded bank in our sample and identify 186 banks.

Online Traffic/Total Dep	The ratio of online traffic (visits to bank website) in December 2022 to the total domestic deposits at the end of 2022. Online traffic data are collected from Semrush, and total domestic deposits are from call reports.
Urban	Indicator for a county being an urban area based on population above 100,000 using data from ACS. Bank-level data are aggregated by averaging values for all branches with weights equal to the value of the branch's deposits.
Log County Income	Logarithm of county's median income using data from ACS. Bank-level data are aggregated by averaging values for all branches with weights equal to the value of branch's deposits.
Age 60+	Share of county's population aged 60 or more using data from ACS. Bank-level data are aggregated by averaging values for all branches with weights equal to the value of branch's deposits.
Higher Education	Share of county's population with bachelor's degree or higher level of education using data from ACS. Bank-level data are aggregated by averaging values for all branches with weights equal to the value of branch's deposits.
Deposit Rate 12MCD10K and 24MCD100K	The average of APY of 12-month (24-month) CD with a minimum of $10k (12MCD10K) or $100k (24MCD100K) deposit during 2022 at the BHC level. The rates data are from RateWatch. We link the RateWatch data with the branches in the Summary of Deposits through the branch identifier. For the two well-represented deposit products, we take the average of the APY across all branches in a certain year.

A.2. Job Postings Data and STM Application

Granular job posting data is provided by Lightcast, which offers a near-complete universe of online job advertisements consistently from 2010 onward. Lightcast curates the dataset by removing duplicates and standardizing entries. We manually match our 2022 sample of bank holding companies (including their subsidiaries) to employer names in the Lightcast database. This process yields approximately 6 million job postings spanning the period from 2010 to 2022. Each posting includes such information as employer name, job title, occupation code, required education, and—most important—required skills, which Lightcast extracts and codes from the underlying job description text.

The following data entry example is a sample job provided by Lightcast.

Appendix Table A.2.a

JobID	Employer	Skills
X	Bank A	Scrum (Software Development)|Non-Verbal Communication|Information Technology|Management|Prioritization|Agile Methodology|Business Valuation|Communication|Collaboration|Sprint Planning|Sprint Retrospectives|New Product Development|Computer Science

To capture the different aspects of a certain job, we use the STM package developed by Roberts et al. (2019) to implement the structural topic model. The STM combines and advances three existing models—CTM, the Dirichlet-Multinomial Regression (DMR) topic model, and the Sparse Additive Generative (SAGE) topic model—to create a semiautomated approach to modeling topics, which can also incorporate covariates and metadata in the analysis of text. This approach is particularly useful for analyzing open-ended textual data.

The input to the model is the complete set of required skills from approximately 6 million job postings associated with our sample banks in 2022, which collectively form the "corpus." In this framework, each job's required skill list constitutes a "document," and each individual skill is treated as a "word." The model identifies 25 latent topics, and the five most probable skills ("words") associated with each topic are listed below (Appendix Table A.2.b). We choose a topic number to be 25 (K = 25) to balance minimizing model residuals and maximizing thematic coherence.

Based on these high-probability words, we classify the 25 topics into six broad categories: Technology, Back-office, Customer-facing, General, Management, and Others. The model also generates a topic score for each job, reflecting the proportion of required skills linked to each topic. These topic scores, which sum to 100 for each job, are shown in the last column of Appendix Table A.2.b for the illustrative job example. Each score indicates the fraction of a job's skill set that is most closely associated with a given topic. For instance, 63% (7 + 51 + 4 +1) of skills are associated with Technology and 16% (3 + 2 + 2 + 2 + 3 +4) of skills are managerial. To build a bank-quarter-level measure of banks' labor demand, we sum the topic scores for the six categories across all jobs posted by a certain bank and scale it by the total job postings by the same bank in a given quarter. We are able to construct the labor demand measure for about 85% of the public banks in our sample.

Appendix Table A.2.b Topic Model Outputs

topic#	Categories	High Probability Words	Topic Score for Job X
10	Technology	trouble shooting, problem solving, information technology, business requirements, operating systems, systems development lifecycle	7
11		agile methodology, scrum software development, innovation, communication, product management	51
17		Java programming language, agile methodology, software development, software engineering, computer science	4
24		SQL programming language, data analysis, statistics, SAS software, data management	1
7	Back-office	Microsoft Excel, Microsoft PowerPoint, Microsoft Outlook, Microsoft Word, ability to meet deadlines	1
12		risk management, auditing, governance, regulatory compliance, risk analysis	1
19		finance, accounting, economics, securities finance, capital markets	0
25		bank secrecy act, mathematics, spreadsheets, clerical works, anti-money laundering	1
1	Customer Facing	mortgage loans, loans, customer service, sales, financial services	0
3		customer service, cash handling, sales, balancing ledger billing, cross selling	4
9		professionalism, customer inquiries, loans, check cashing, sales	1
21		product knowledge, customer service, effective communication, business objectives, time management	1
22		sales, sales prospecting, commercial banking, business development, cross selling	1
8	General	writing, communication, interpersonal communications, problem solving, financial services	3
14		detail oriented, multitasking, verbal communication skills, organizational skills, time management	3
15		problem solving, communication, self-motivation, critical thinking, financial services	4
2	Management	presentations, management, influencing skills, planning, consulting	3
4		management, writing, communication, Microsoft Office, presentations	2
13		marketing, new product development, product management, Master of Business Administration (MBA), marketing strategies	2
16		leadership, coaching, management, operations, mentorship	2
20		operations, coordinating, research, management, workflow management	3
23		project management, process improvement, leadership, planning, influencing skills	4
5	Other	mortgage loans, loans, real estate, underwriting, loan origination	0
6		investments, wealth management, FINRA series 7 general securities representative, brokerage, financial industry regulatory authorities	1
18		loans, underwriting, accounting, commercial lending, collections	0

Appendix B. The Role of Brokered Deposits

This appendix analyzes the role that brokered deposits played in the 2023 banking crisis and their relation to banks with low branch density. The FDIC (2011) classifies a brokered deposit as "any deposit that is obtained, directly or indirectly, from or through the mediation or assistance of a deposit broker." Brokered deposits became relevant in the early 1960s, and as banking technology developed further, relying on brokered deposits became a feasible alternative to owning and operating physical branches. Figure A2 demonstrates that banks with lower branch density have a higher share of brokered deposits in their total deposits. Specifically, for banks with density below 2.5, brokered deposits constitute over 18% of total deposits, compared to only 2% for banks with density above 10.

Brokered deposits have been historically perceived as a volatile source of funding and are commonly associated with excessive risk-taking by banks. For example, the FDIC has expressed concerns over brokered deposits for decades and indeed regulates brokered deposits differently than core deposits. However, the evidence on whether the reliance on brokered deposits affects bank performance, especially bank failure, is mixed (see Barth et al. (2020) for a review). Indeed, the FDIC (2011) recognizes that brokered deposits per se are not a problem and rather recommends that "the proper use of such deposits should not be discouraged."

In terms of bank run risk, brokered deposits can be viewed as more stable than core deposits.[1] Core deposits are exposed to on-demand, immediate withdrawals, whereas brokered deposits have predetermined maturity and do not permit early withdrawals unless the depositor dies or is declared legally incompetent. In addition, when faced with the prospects of large withdrawals, some banks resort to brokered deposits as a fast, yet more expensive alternative source of funding (Heeb and Eisen (2023)). For instance, Western Alliance, one of the banks that suffered severe stock price drops during the 2023 banking crisis, showed an increase in its brokered deposits from $4.79 billion (or 8.89% of total deposits) in Q4 2022 to $18.28 billion (or 35.64% of total deposits) in Q2 2023. We next formally test the relation between branch density, brokered deposits, and deposit outflows.

[1] FDIC Vice Chairman Travis Hill (2023) has recognized the stickiness of brokered deposits: "Far from being 'hot money,' these deposits are so cold they are virtually frozen in place."

We regress (i) the share of brokered deposits; (ii) the change in the brokered deposits share between Q4 2022 and Q2 2023; and (iii) the log change in the value of brokered deposits over the same period on our measure of branch density and the set of control variables used in our main specification. Table AVII reports the results. Brokered deposits account for a higher fraction of funding for banks with lower branch density (column (1)), and this pattern becomes more pronounced following the banking turmoil in early 2023 (column (2)). However, the increase in the share of brokered deposits does not imply that low-density banks proactively increased the level of brokered deposits. Combined with the results in column (3), which shows the relative decline in the level of brokered deposits for banks with lower branch density, brokered deposits also experienced outflows, though not as severe as other sources of funding.

Appendix B References

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Federal Deposit Insurance Corporation (FDIC), 2011, Study on core deposits and brokered deposits, Submitted to Congress pursuant to the Dodd-Frank Wall Street Reform and Consumer Protection Act.

Heeb, Gina, and Ben Eisen, 2023, Banks lean on "hot" deposits to shore up balance sheets, *Wall Street Journal,* July 31.

Hill, Travis, 2023, Remarks by FDIC Vice Chairman Travis Hill at the Cato Institute on "Insights on the FDIC's agenda," https://www.fdic.gov/news/speeches/2023/spsept2123.html.

Appendix C. Branch Density, Stock Prices and Deposit Rates, 2000-2020

Our analysis in the paper has focused on the role of branch density in explaining banks' performance during the 2023 banking crisis. In this appendix, we examine the role that branch density played in different time periods. That is, we put the branch density to test out of sample. Naturally, branch density evolved over time, and the customer selection channel we emphasize likely became relevant only with the advancement of digital technologies. Accordingly, we do not expect branch density to be linked to higher deposit outflow risk in earlier decades. Nevertheless, as shown below, branch density has been associated with banks' characteristics and performance over the past two decades. We illustrate this in three steps, analyzing the relationship between historical branch density and stock market performance, deposit rates, and deposit growth.

In columns (1) and (2) of Table AVIII, we examine the relationship between branch density and risk exposure, measured by the sensitivity of a bank's stock returns to shocks affecting the broader banking sector. Column (1) shows that banks with branch density below 2.5 experience 1.1 percentage point lower returns on bad days for the banking sector. Bad days are defined as those in the bottom 1% of the distribution of equally weighted daily returns for the banking sector. Column (2) shows that banks with higher branch density exhibit 0.8 percentage point higher returns on good days, defined analogously as days in the top 1% of the distribution. These estimates are based on data from 2000 to 2022, suggesting that banks with lower branch density have historically exhibited greater volatility of returns, even outside the 2023 banking crisis. The specifications include bank fixed effects, supporting the interpretation of branch density as a key indicator of this heightened risk.

The fact that the absolute value of the abnormal return is higher on "bad days" may suggest that branch density is particularly related to higher downside risk. However, this pattern is only suggestive, as the abnormal return on good days is also large and significant, while the difference between the absolute values of abnormal returns on bad and good days is not statistically significant.

Columns (3) and (4) analyze the relationship between branch density and deposit rates over the period 2000 to 2022. Consistent with the findings in Table VI, which show that banks with low branch density offered higher deposit rates in early 2023, we find that these banks consistently offered higher deposit rates throughout the period 2000 to 2022. Specifically, banks in the low-density group paid between 0.17 and 0.36 percentage points more than other banks, while the median deposit rate during this period was 1.00% (with a mean of 1.5%). This indicates that the business model of low-density banks has been associated with higher deposit rates not only in times of stress but also during periods of stable deposit growth. This pattern is consistent with a long-term strategy focused on attracting more sophisticated and price-sensitive customers.

Finally, columns (5)–(8) analyze the relation between branch density and deposit flows between 2000 and 2020. This analysis is less straightforward because changes in deposit volume influence branch density in the subsequent period, making the interpretation of coefficients in a panel regression of deposit growth on contemporaneous branch density unclear. To address this challenge, we regress deposit growth on the initial branch density. In columns (5) and (7), we do this for the years 2000 to 2010, while in columns (6) and (8), we analyze the years 2011 to 2020.

Initial branch density positively predicts uninsured deposit growth in the decade 2011to 2020 that directly precedes the 2023 crisis, consistent with the idea that a business model based on low branch density helped banks grow their deposits during good times. The pattern is significant for uninsured deposits in column (6), while the coefficient is positive but insignificant for insured deposits (column (8)), which suggests that the low-density banking model has been more successful among more sophisticated customers with large deposits. In the previous decade, the same relationship is not visible (columns (5) and (7)), which suggests that a business model based on limited branches started to generate abnormal deposit growth only over the last decade, coinciding with technological advances that have made banking without many branches feasible and more convenient. Earlier low branch density might have been simply an inconvenience that put banks at a disadvantage.

Overall, Table AVIII demonstrates that branch density has been correlated with banks' performance and characteristics of their business model not only during the 2023 banking crisis but also over the last two decades. Thus, low branch density is likely to be an important determinant of bank susceptibility to deposit outflows in other settings and periods as well.

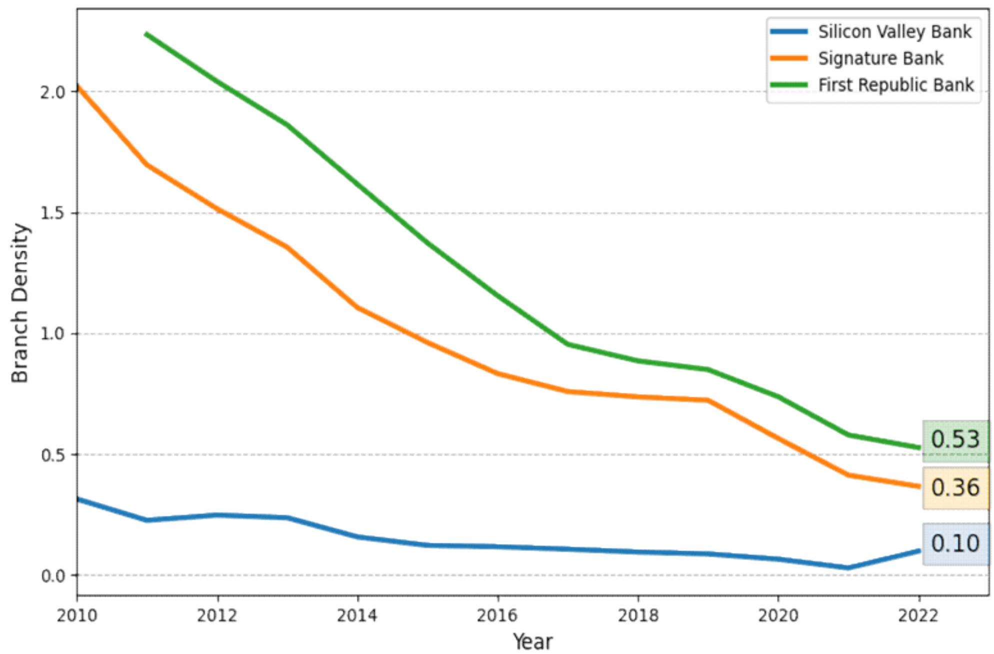


Figure A1. Branch Density and Failed Banks. This figure shows the branch density of Silicon Valley Bank, Signature Bank, and First Republic Bank from 2010 to 2022. Branch density is defined as the number of branches per $1 billion in deposits, with deposits adjusted for inflation and expressed in 2022 dollars. Branch density values as of June 2022 are annotated at the end of each line. Because First Republic Bank was established in July 2010, data for this bank are available only from 2011 onward. Source: Summary of Deposits.

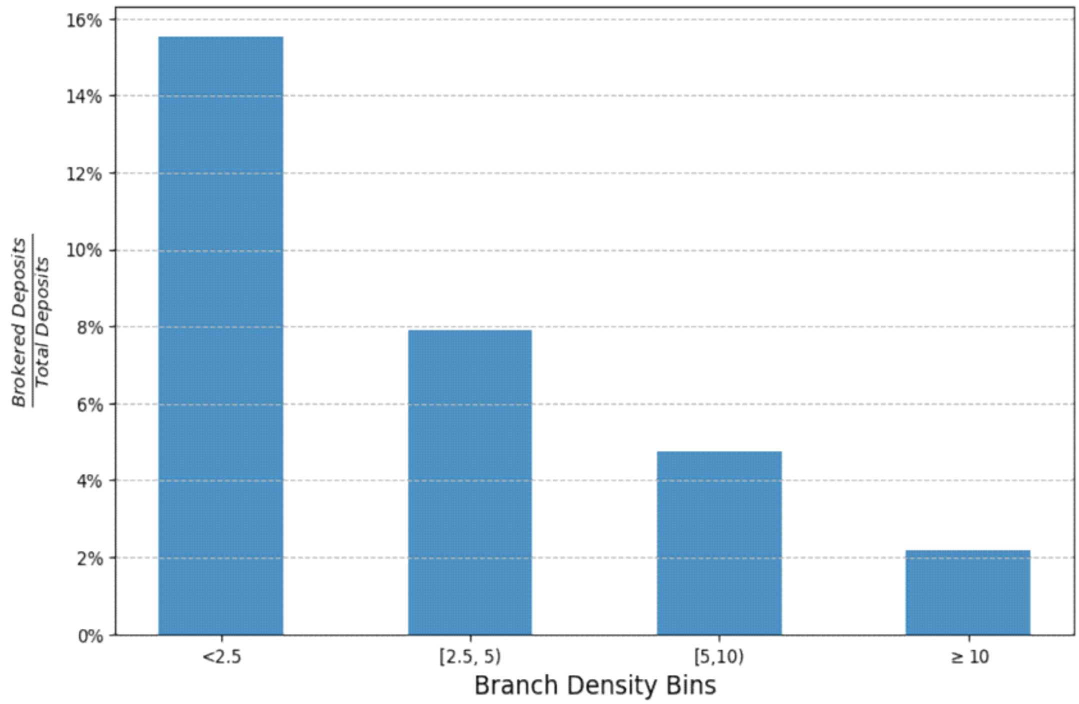


Figure A2. Brokered deposits and branch density. This figure plots the share of brokered deposits in total deposits across branch density bins for all FDIC-insured bank holding companies from 2010 to 2022. Branch density is defined as the number of branches per $1 billion in total deposits expressed in 2022 dollars. Branch density is categorized into four bins: <2.5, [2.5, 5), [5,10), and ≥ 10. Each bar represents the average share of brokered deposits—expressed as a percentage of total deposits—within each branch density bin.

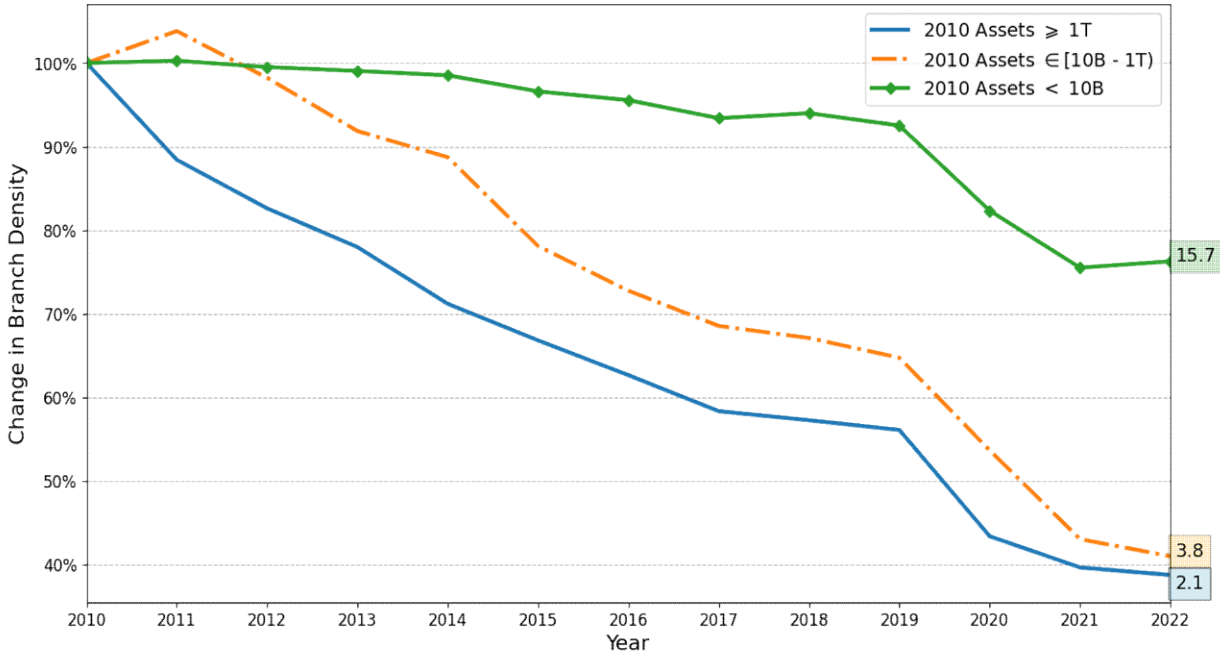
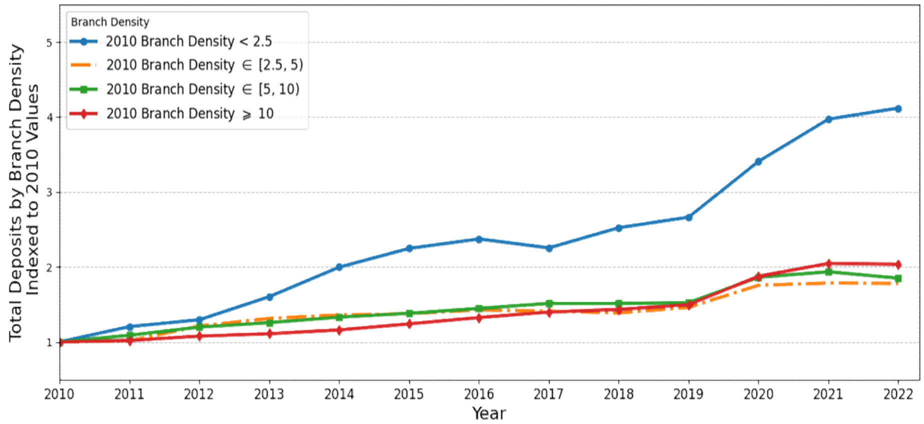
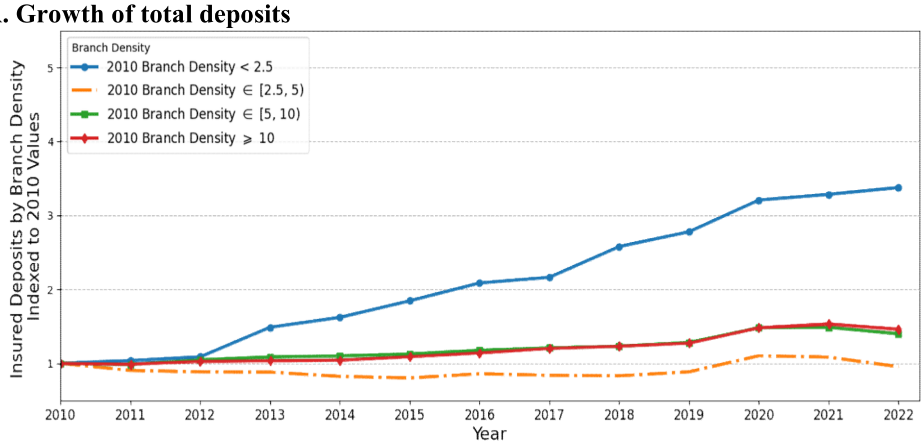


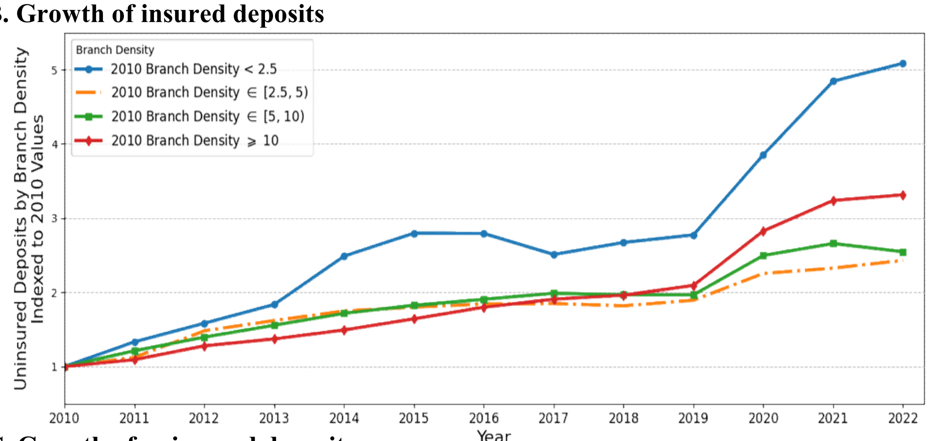
Figure A3. The evolution of branch density by bank size. The figure illustrates the decline in branch density across bank size groups. Branch density is defined as the number of branches per $1 billion in deposits. Deposit amounts are adjusted for inflation and reported in 2022 dollars. The sample includes all FDIC-insured bank holding companies, categorized into three size groups based on their total assets at the end of 2010: (1) $1 trillion or more, (2) $10 billion to less than $1 trillion, and (3) less than $10 billion. The median branch density within each group is plotted over time, with the 2022 values annotated for each group. Source: Summary of Deposits.



Panel A. Growth of total deposits



Panel B. Growth of insured deposits



Panel C. Growth of uninsured deposits

Figure A4. Deposits growth and branch density. This figure plots the average values of total deposits (Panel A), insured deposits (Panel B), and uninsured deposits (Panel C) for bank holding companies, grouped by branch density and indexed to their 2010 levels. Deposit amounts are adjusted for inflation and reported in 2022 dollars. Branch density is calculated as the number of branches per $1 billion in total deposits. Bank holding companies are divided into four groups based on their 2010 branch density: less than 2.5; 2.5 to less than 5; 5 to less than 10; and 10 or more. Group composition is fixed over time.

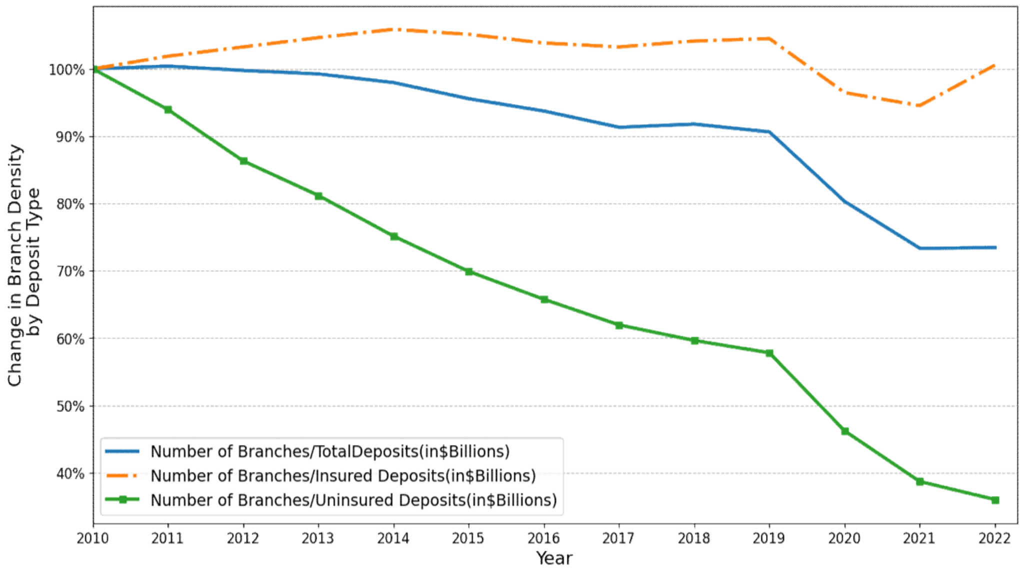


Figure A5. Branch density by deposit types. This figure illustrates how branch density varies depending on the type of deposits considered—total deposits, insured deposits, or uninsured deposits—over the period from 2010 to 2022. Branch density is measured as the number of bank branches per $1 billion in deposits of the relevant type. Deposit amounts are adjusted for inflation and reported in 2022 dollars. The sample includes all bank holding companies insured by FDIC.

Table AI

Sample Banks by Branch Density Bin in 2022

Notes: Branch density is defined as the number of branches per $1 billion in deposits as of June 2022 and is categorized into four bins: <2.5, [2.5, 5), [5, 10), and ≥10. Within each bin, five selected banks are presented. The bottom panel highlights banks that were severely affected during the 2023 distress episodes. Banks marked with * are not bank holding companies; for these, bank-level data from call reports is used.

Bank Name	Branch Density	#Branches	Deposits($B)
Branch Density <2.5			
Average for the Group	0.77	342	261
CAPITAL ONE FINANCIAL	0.74	297	399
NORTHERN TRUST CORPORATION	1.06	58	55
JPMORGAN CHASE & CO.	2.26	4,819	2128
EAST WEST BANCORP, INC.	2.04	106	52
GOLDMAN SACHS GROUP, INC., THE	0.01	5	343
Branch Density [2.5, 5)			
Average for the Group	3.72	538	140
HOPE BANCORP, INC.	3.58	54	15
OCEANFIRST FINANCIAL CORP.	4.04	42	10
U.S. BANCORP	4.94	2,251	455
WELLS FARGO & COMPANY	3.24	4,768	1465
BANK OF HAWAII CORPORATION	2.57	54	20
Branch Density [5, 10)			
Average for the Group	7.13	366	54
FB FINANCIAL CORPORATION	8.72	92	11
FIRST HORIZON CORPORATION	5.75	415	72
COMMERCE BANCSHARES, INC.	5.78	164	28
PNC FINANCIAL SERVICES GROUP, INC., THE	5.84	2,615	447
KEYCORP	6.64	999	149
Branch Density >=10			
Average for the Group	12.16	191	16
INTERNATIONAL BANCSHARES CORPORATION	13.13	174	13
NBT BANCORP INC.	13.90	142	10
RENASANT CORPORATION	11.28	157	14
NORTHWEST BANCSHARES INC	12.16	151	12
TRUSTMARK CORPORATION	12.53	187	15
Affected Banks			
SVB FINANCIAL GROUP	0.1	17	175
SILVERGATE CAPITAL CORPORATION	0.15	2	14
SIGNATURE BANK*	0.36	38	104
FIRST REPUBLIC BANK*	0.53	87	166
WESTERN ALLIANCE BANCORPORATION	0.67	36	54
PACWEST BANCORP	2.1	72	34

Table AII
Evolution of Bank Branches in the United States

Notes: The sample covers the years 2010 to 2022. The regression in column (1) is at the year level, while that in column (2) is at the bank-quarter level. The dependent variable is the number of branches in all banks (column (1)) or of a given bank (columns (2)–(4)). Year is a continuous variable, while Covid Years is an indicator for year 2020 and beyond. The sample in columns (2)–(4) is limited based on the average level of banks' deposits from 2010 to 2022. Column (2) includes banks with average deposits of less than \$10B, column (3) includes those with average deposits between \$10B and \$1T, and column (4) includes those above \$1T. Robust standard errors in parentheses in columns (2)–(4). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)
	Number of Branches			
	All Banks	Small Banks	Medium Banks	Large Banks
Year	-611.0***	0.181***	-2.587**	-109.7***
	-150.6	-0.007	-1.019	-20.7
Covid Years	-4201.3**	0.194***	2.347	-159.4
	-1337.6	-0.061	-9.49	-134.6
N	13	54,402	1,142	39
R^2		0.969	0.978	0.875

Table AIII
Integrating the Evidence

Notes: Panel A reports correlation coefficients between bank-level variables: branch density, index of demand for technological skills from job postings, 2010-2017 growth in IT budgets from Aberdeen, deposit rate for $10k deposit of 12 months duration from Rate Watch, share of education with higher education, and log average county income (both based on ACS and location of bank's branches). Panel B reports regressions of depositor-level measures of rate sensitivity on depositor measures of financial technology adoption, and vice versa. Rate sensitivity is defined as whether the consumer reports that interest rates are an important factor in choosing among banks. Technology index is defined as the average of two indicators, one for whether the consumer has made a payment on Zelle, Cash App, or Venmo in the past 30 days and one for whether the consumer uses mobile banking. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A. Bank-Level Correlations

	Branch Density	Tech Skills Demand	IT Growth	Deposit Rate 12M10K	Higher Education	Log(Income)
Branch Density	1					
Tech Skills Demand	-0.369*	1				
IT Growth	-0.170*	0.203*	1			
Deposit Rate 12M10K	-0.116*	0.314*	0.256*	1		
Higher Education	-0.036*	0.212*	0.118*	0.079*	1	
Log(Income)	-0.011	0.140*	0.075*	0.043*	0.749*	1

Panel B. Depositor-Level Regressions in the MRI Data

	Rate Index		Technology Index	
	(1)	(2)	(3)	(4)
Technology Index	11.25***	8.94***		
	(0.55)	(0.58)		
Rate Index			5.92***	4.57***
			(0.29)	(0.28)
Log Household Income		2.68***		4.90***
		(0.25)		(0.17)
Age 60+		-4.32***		-24.84***
		(0.53)		(0.36)
Higher Education		1.22***		1.96***
		(0.43)		(0.30)
N	63,252	63,252	63,252	63,252
Zip-3 FE	X	X	X	X
Bank FE	X	X	X	X

Table AIV
Alternative Measures of Branch Density

Notes: Columns (1), (2), (5), (6), (9), and (10) present specifications analogous to columns (3) and (5) in Table VII, while columns (3), (4), (7), (8), (11), and (12) present specifications analogous to columns (1) and (2) from Table VIII for alternative measures of bank branch density: number of branches/value of uninsured deposits (mean 21.5, std dev 13.9) in columns (1)–(6), and logarithm of number of branches/value of brokered deposits in columns (7)–(12) (mean 0.81, std dev 2.92). The thresholds for defining lowest, low, and medium groups for different measures are: 5, 10, and 20 (branches/uninsured deposits); 25, 100, 200 (branches/brokered deposits); and 2.5, 5, 10 (selected branches/deposits). Controls and standard errors are as in Table VII. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Return	Return	Large Dep Outflow		Return	Return	Large Dep Outflow		Return	Return	Large Dep Outflow	
	(SVB)	(First Republic)	Unins	Insured	(SVB)	(First Republic)	Unins	Insured	(SVB)	(First Republic)	Unins	Insured
Lowest Br Dens	-11.25***	-3.119***	9.399**	9.442***	-10.71***	-3.138*	18.68***	11.38***	-10.83***	-2.793*	13.08***	12.35***
	(1.969)	(1.169)	(3.738)	(3.456)	(3.016)	(1.643)	(4.811)	(4.117)	(2.435)	(1.428)	(3.957)	(3.720)
Low Br Dens	-4.501***	-2.314***	0.957	3.094	-3.147***	-0.186	3.739	6.516**	-5.559***	-1.874**	1.438	0.432
	(1.410)	(0.842)	(2.522)	(2.377)	(1.047)	(0.712)	(2.572)	(2.705)	(1.388)	(0.751)	(2.358)	(1.966)
Medium Br Dens	-1.331	-1.256*	-3.564**	1.320	-3.475**	-1.293	3.280	3.540	-1.356	-1.364**	-0.0732	1.460
	(0.975)	(0.720)	(1.412)	(1.486)	(1.503)	(1.479)	(2.748)	(2.658)	(0.824)	(0.637)	(1.320)	(1.307)
Log(Assets)	-0.753	-0.0811	-0.389	-1.438*	-0.971**	-0.167	0.284	-0.742	-0.801*	-0.117	-0.698	-1.669**
	(0.463)	(0.231)	(0.857)	(0.833)	(0.451)	(0.242)	(0.952)	(0.947)	(0.441)	(0.231)	(0.862)	(0.822)
Dep/Assets	-20.38***	-6.024	3.401	-7.916	-23.74**	-12.13***	26.97**	3.739	-20.94***	-5.383	4.312	-6.277
	(7.558)	(3.808)	(9.741)	(9.045)	(9.555)	(4.477)	(13.56)	(13.44)	(6.776)	(3.704)	(9.835)	(8.807)
Insured Dep	6.646	3.343	-7.824	5.159	13.03**	9.556***	-9.532	5.822	8.938**	4.179*	-6.621	2.326
/Total Dep	(4.608)	(2.537)	(5.467)	(5.521)	(5.224)	(3.533)	(7.283)	(7.484)	(4.315)	(2.497)	(4.953)	(4.945)
MTM Losses	-14.40	-29.51**	-15.09	-25.22*	-21.74	-30.49***	13.66	-21.08	-13.26	-28.86**	-14.34	-24.34*
	(11.65)	(12.29)	(12.17)	(13.21)	(16.95)	(11.23)	(20.47)	(20.69)	(12.02)	(12.46)	(12.21)	(13.20)
Dep Growth	-2.796**	0.234	1.474***	-0.264	-3.946*	-0.391	1.488***	-0.307	-2.789**	0.114	1.581***	-0.178
2019-2022	(1.417)	(0.499)	(0.375)	(0.164)	(2.016)	(0.727)	(0.333)	(0.220)	(1.235)	(0.475)	(0.356)	(0.175)
Density Measure	Branches/Uninsured Deposits				Branches/Brokered Deposits				Selected Branches/Deposits			
N	313	311	3,368	3,367	214	212	1,266	1,266	314	312	3,368	3,368
R^2	0.363	0.190	0.021	0.033	0.344	0.203	0.046	0.039	0.347	0.184	0.020	0.035
Size controls	X	X	X	X	X	X	X	X	X	X	X	X

Table AV
Branch Density with Additional Controls

Notes: Columns (1), (2), (5), and (6) present specifications analogous to columns (3) and (5) in Table III, while columns (3), (4), (7), and (8) present specifications analogous to columns (1) and (2) from Table IV with additional control variables included: share of commercial real estate loans in bank's assets, share of provisions for bad loans in bank's assets, profitability in 2021, expected shortfall, cash to assets (columns (1)-(4)); and supply-driven deposit change and share of bank's deposits in the county where that bank has the most deposits (columns (5)-(8)). Remaining controls and standard errors as in Tables VII and VIII.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Return	Return	Large Dep Outflow		Return	Return	Large Dep Outflow	
	(SVB)	(First Republic)	Unins	Insured	(SVB)	(First Republic)	Unins	Insured
Branch Dens < 2.5	-11.46***	-3.987**	28.24**	15.45	-8.982***	-2.696	13.42***	8.404*
	(3.162)	(1.873)	(11.88)	(11.02)	(3.433)	(1.957)	(5.045)	(4.329)
Branch Dens [2.5, 5)	-5.675***	-1.710*	1.914	-2.032	-4.939***	-0.917	0.741	-0.445
	(1.824)	(0.903)	(7.757)	(5.235)	(1.456)	(1.015)	(2.727)	(2.306)
Branch Dens [5, 10)	-1.895	-0.906	0.526	1.416	-1.601**	-1.106	-0.859	1.273
	(1.158)	(0.814)	(4.268)	(5.252)	(0.796)	(0.689)	(1.499)	(1.501)
NPL/Assets	-60.34	-54.03	228.4	-215.5				
	(261.4)	(96.72)	(910.7)	(915.5)				
CRE Loans/Assets	12.81	-6.752	-29.22	-21.68				
	(9.252)	(6.354)	(33.17)	(30.09)				
Profitability (*t*-1)	318.2***	111.1**	-499.8	-415.9*				
	(69.67)	(47.88)	(356.0)	(239.5)				
Expected Shortfall	-26.44**	-13.84**	20.99	-16.63				
	(12.21)	(6.965)	(35.71)	(44.57)				
Cash/Assets	32.81***	15.09**	-92.80	22.64				
	(12.27)	(7.374)	(59.06)	(51.60)				
Dep/Assets	-21.69***	-6.437	16.68	16.78	-12.92	-5.091	11.00	-4.142
	(7.458)	(4.752)	(43.41)	(23.22)	(8.169)	(4.322)	(10.17)	(9.412)
Ins Dep/Total Dep	14.36**	6.555**	-25.40	6.916	10.28**	6.954**	-4.784	0.856
	(5.832)	(2.964)	(21.50)	(19.37)	(4.181)	(2.884)	(5.167)	(5.205)
MTM Losses	-1.771	-16.74*	68.92	-54.73	-10.57	-33.75**	-12.66	-29.98**
	(16.43)	(8.956)	(63.65)	(48.61)	(11.47)	(13.13)	(13.05)	(13.83)
Dep Growth 2019-2022	-3.256**	-0.375	-0.698	-5.550*	-2.238*	0.0608	1.798	-1.672
	(1.343)	(0.725)	(5.171)	(2.851)	(1.334)	(0.486)	(2.281)	(1.092)
Supply Driven Dep Ch					0.00475	-0.00772	47.29	-0.0273
					(0.0265)	(0.0101)	(37.43)	(0.0259)
% Deposit in 1 County					-2.323	-1.402	2.071	4.049
					(2.384)	(2.028)	(2.889)	(2.685)
N	198	198	281	282	302	300	3098	3099
R^2	0.325	0.200	0.080	0.092	0.351	0.215	0.021	0.032
Size controls	X	X	X	X	X	X	X	X

Table AVI
Branch Density and Stock Prices with Alternative Return Windows

Notes: The specifications presented are as in Table VII, columns (3) and (5), except that stock returns are defined using alternative windows as described below the dependent variable names.

	(1)	(2)	(3)	(4)	(5)
		Stock Return (SVB)		Stock Return (First Republic)	
	3/06-3/15	3/10-3/13	3/01-3/15	04/28-05/04	05/01-05/04
Branch Density < 2.5	-8.530***	-4.698**	-9.518***	-4.666*	-3.727
	(2.261)	(1.833)	(2.506)	(2.514)	(2.287)
Branch Density [2.5, 5)	-4.271**	-4.024***	-4.883***	-2.428**	-1.363
	(1.719)	(1.047)	(1.736)	(0.998)	(0.858)
Branch Density [5, 10)	-0.999	-1.438**	-0.713	-3.558***	-2.833***
	(1.067)	(0.581)	(1.094)	(0.946)	(0.790)
Log(Assets)	-1.814***	-0.277	-1.676***	-0.279	-0.293
	(0.535)	(0.295)	(0.573)	(0.342)	(0.291)
Dep/Assets	-22.26***	-13.27***	-24.58***	-0.297	-0.856
	(7.382)	(4.418)	(8.379)	(4.452)	(3.722)
Insured Dep/Total Dep	9.326	5.458*	14.39**	3.717	3.846
	(6.110)	(3.089)	(6.001)	(4.174)	(3.414)
MTM Losses	-16.13	-1.095	-25.87*	-33.69**	-26.00**
	(15.13)	(8.750)	(14.56)	(13.61)	(12.93)
Dep Growth 2019-2022	-3.004**	-0.708	-3.351*	-0.102	-0.584
	(1.496)	(0.613)	(1.825)	(0.838)	(0.723)
N	315	315	315	314	315
R^2	0.323	0.198	0.323	0.166	0.158
Size FE	X	X	X	X	X

Table AVII
Branch Density and Brokered Deposits

Notes: The outcome variables are the fraction of brokered deposits of total deposits (column (1)), change of brokered deposits as a fraction of total deposits from Q4 2022 to Q2 2023 (column (2)), and change in the logarithm of the amount of brokered deposits from Q4 2022 to Q2 2023 (column (3)). All outcome variables are multiplied by 100 to improve coefficient readability. Changes in the share of brokered deposits and in log of brokered deposits are winsorized at the 1st and 99th percentiles. Branch Density is the number of branches per $1 billion in total deposits. All columns include control for logarithm of total assets and for fixed effects for five total assets quintiles, deposits/asset ratio, share of insured deposits, mark-to-market (MTM) losses estimates, and 2019 to 2022 deposits growth. Robust standard errors in parentheses.

	(1)	(2)	(3)
	Brokered Dep /Total Dep	ΔBrokered Dep/Total Dep Q4/22-Q2/23	Δlog(Brokered Dep) Q4/22 – Q2/23
Branch Density < 2.5	10.99***	0.917**	-0.289***
	(1.782)	(0.412)	(0.109)
Branch Density [2.5, 5)	5.299***	0.989***	-0.0813
	(0.783)	(0.258)	(0.0982)
Branch Density [5, 10)	2.548***	0.392***	0.00998
	(0.359)	(0.122)	(0.0709)
Log(Assets)	-0.582***	-0.0807	0.0557*
	(0.213)	(0.0773)	(0.0301)
Dep/Assets	-18.21***	-2.864***	-0.307
	(2.881)	(0.777)	(0.381)
Insured Dep/Total Dep	6.396***	-0.529	-0.917***
	(1.829)	(0.396)	(0.198)
MTM Losses	-0.782	3.011***	2.608***
	(2.802)	(0.896)	(0.611)
Dep Growth 2019-2022	0.274	-0.0306	-0.0199
	(0.300)	(0.0476)	(0.0469)
N	3,369	3,369	1,214
R^2	0.194	0.090	0.072
Size controls	X	X	X
Sample	All	All	All

Table AVIII
Branch Density over 2000-2020

Notes: Dependent variables include daily stock returns (columns (1) and (2)), deposit rates for 12-month CDs with a $10K minimum (columns (3) and (4)), and quarter-to-quarter growth rates of uninsured and insured deposits (columns (5)–(8)). The key independent variables are indicators for branch density below 2.5, interacted with: (i) an indicator for banking sector returns in the bottom 1% (bad days), and (ii) an indicator for returns in the top 1% (good days). The first three rows use a time-varying branch density measure, while the last two use density fixed as of 2000 and 2010, respectively. Columns (5) and (7) restrict the sample to 2000–2010, and columns (6) and (8) to 2010–2022. In all regressions—consistent with the main specification in Table III—indicator variables for branch density in the [2.5, 5) and [5, 10) intervals are included both as level terms and, where applicable, as interactions with the good/bad day indicators. The omitted category is branch density ≥10. Additional controls include log(total assets), fixed effects for five size quintiles (all columns), bank fixed effects (columns (1), (2), and (4)), and deposit-to-assets and insured-deposits-to-total-deposits ratios (columns (3)–(8)). The unit of observation is bank-day (columns (1) and (2)), bank-week (columns (3) and (4)), and bank-quarter (columns (5)–(8)). All columns use unbalanced panels. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Daily Return		Deposit Rate		Deposit Change			
					Uninsured		Insured	
Bad Day ×	-0.0109***							
Branch Density < 2.5	(0.00275)							
Good Day ×		0.00808**						
Branch Density < 2.5		(0.00324)						
Branch Density < 2.5			0.360***	0.168***				
			(0.0114)	(0.0143)				
Branch Density(2000)					-0.250		-2.920***	
< 2.5					(0.751)		(0.537)	
Branch Density(2010)						1.077**		0.240
< 2.5						(0.485)		(0.317)
N	1,102,063	1,102,063	347,075	347,075	169,365	168,428	169,467	168,538
R^2	0.328	0.328	0.929	0.959	0.180	0.037	0.327	0.069
Sample Period		2000-2022			2000-10	2010-20	2000-10	2010-20
Bank FE	X	X		X				
Size Controls	X	X	X	X	X	X	X	X
Dep/Assets, % Insured Dep			X	X	X	X	X	X