

# When Banks Fail: Depositor Attention and the Cost of Funding for Survivors\*

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## ABSTRACT

A bank failure significantly disrupts the local deposit market. Despite a competitor exit, surviving banks raise deposit rates while their deposit growth falls. Comparing branches of the same bank located in counties with and without a nearby failure, we find that advertised one-year CD rates rise significantly, while annual deposit growth falls. Consistent with an inward shift in local deposit demand that raises survivors' marginal funding costs, aggregate county-level deposit growth also declines, households reallocate funds toward interest-generating alternatives, and surviving banks reduce mortgage originations, especially those with high predetermined funding exposure.

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## I. Introduction

What happens to local deposit competition when a bank fails? On the one hand, the exit of a competitor may lessen competition for deposits, allowing surviving banks to exercise greater market power. On the other hand, bank failures differ from ordinary firm exits: they often occur during crisis periods, and their high-profile nature may draw attention to banking relationships that depositors would otherwise rarely reconsider, causing them to “wake up” and reassess both their banks and outside investment opportunities. These competing forces make the overall effect of bank failures on local deposit competition theoretically ambiguous.

Despite an extensive literature on deposit competition, relatively little is known about how local deposit competition responds to bank failures. The central challenge is identification. While bank failures generate an abrupt change in the local competitive environment, they also coincide with periods of financial stress, which can affect depositors through alternate channels related to deposit demand and banks’ funding decisions, making it difficult to isolate the effects of the failure itself.

In this paper, we address this challenge by exploiting the geographic structure of bank branch networks. Our empirical design compares branches of the same bank in the same year that operate in counties with and without a nearby bank failure. Specifically, our specification includes bank-by-year fixed effects, which absorb bank-wide funding conditions, balance-sheet shocks, and pricing decisions. We additionally include county fixed effects to absorb permanent differences across local markets, and time-varying county controls to account for local economic conditions. Our identification therefore comes from the differential changes across branches of the same bank that face different local failure environments.

To implement this design, we combine bank failure data from Federal Deposit Insurance Corporation (FDIC) with branch-level advertised deposit rates from RateWatch and branch deposits from the FDIC Summary of Deposits (SOD). In the resulting analysis, we find that one-year \$100,000 certificate of deposit (CD) rates rise by 3.4 basis points (around 15% of the sample standard deviation) after a nearby bank failure and remain elevated for several years. Quantity moves in the opposite direction; annual deposit growth at surviving branches falls, despite higher advertised rates.

Importantly, this joint price-quantity response indicates an inward shift in local deposit demand. In particular, our findings are inconsistent with surviving banks using higher deposit rates to attract newly available customers following a competitor failure. They are also inconsistent with banks deliberately accommodating lower deposit growth by reducing deposit rates. Instead, we interpret our finding as evidence that a bank failure, a highly salient local event, “wakes up” sleepy depositors. This prompts depositors to reallocate their funds elsewhere, and surviving banks respond by raising deposit rates to mitigate the resulting decline in deposit growth.

We conduct several robustness tests. First, because bank failures disproportionately occur in larger and more populous counties, we verify that our results are robust to excluding the smallest and the most populous counties, and to a stacked event-study design that pairs failure counties with never-treated counties matched on pre-failure local economic conditions. Moreover, we conduct placebo tests using two other salient adverse local events: large plant closures and large firm bankruptcies. Like bank failures, these events may signal a severe deterioration in local economic conditions, but unlike bank failures, they do not directly concern depositors or their relationships with local banks. Neither event is associated with deposit rates in the same sample. We interpret this as strong evidence that our results capture a distinct link between bank failures

and local deposit markets, rather than a generic response of deposit rates to salient local economic distress. Finally, our dynamic estimates are robust to alternative event-study estimators (e.g., [Sun and Abraham 2021](#)).

We present several additional pieces of evidence that help validate our empirical design. First, the estimated effects are stronger when the failed bank had a larger pre-failure footprint in the local market, measured using either its share of local deposits or branches. This pattern is consistent with a bank failure having a greater effect when the failed institution represented a more important local competitor. Second, the effects are substantially stronger among surviving banks that exhibited greater geographic variation in deposit rates across their branches before the failure. This result is reassuring for our empirical design, which relies on banks adjusting deposit rates differently across local markets. Third, the effects are largest in the Northeast and West, regions that also tend to exhibit lower deposit rates, potentially reflecting greater scope for the depositor-attention mechanism emphasized in the paper. Finally, we find a pronounced geographic gradient in the response: deposit rates increase most strongly near the failed bank, become smaller at intermediate distances, and are statistically indistinguishable from zero farther away. Together, these patterns provide additional validation that our estimates capture a local response to bank failure.

We further examine the economic mechanism underlying the deposit rate and quantity response. First, we ask where the deposits go. Aggregate county-level deposit growth declines by 3.4 percentage points, indicating that deposits leaving surviving branches are not simply reallocated elsewhere within the local banking system. We find evidence that these funds instead move toward alternative financial assets: taxable interest income per dollar of local deposits increases, as does dividend income relative to adjusted gross income, which is consistent with households reallocating funds toward

higher-yielding interest-bearing assets, including money market funds. The contraction in local deposit funding also translates into real effects. Bank mortgage originations decline following a nearby failure, while nonbank originations do not, resulting in a decline in banks' share of local mortgage lending. Importantly, this lending response is substantially stronger among surviving banks with greater predetermined funding exposure to the failure county. Within the same county-year, mortgage originations decline by around 20 percent more at banks for which the affected county represented a particularly important source of deposits before the failure. Taken together, these results connect the decline in local deposit demand to higher funding pressure at surviving banks, and ultimately, reduced credit provision.

We then examine why deposit demand declines following a nearby bank failure. One possibility is that a failure causes depositors to become more concerned about the riskiness of surviving banks. This explanation predicts a stronger deposit rate response for uninsured deposits, which are more exposed to losses in the event of failure. Instead, the response for uninsured deposits is only about half as large as that for insured deposits. We find a similar pattern across banks: the deposit rate response is concentrated among better-capitalized surviving banks, while the weakest-capitalized banks do not raise rates. These findings are difficult to reconcile with a pure risk-compensation explanation. Instead, we interpret the evidence as consistent with a salient bank failure "waking up" otherwise sleepy depositors and prompting them to reassess their banking relationships and outside investment opportunities. Consistent with this interpretation, consumer complaints increase following a nearby bank failure. Importantly, the increase is concentrated in deposit accounts and mortgages, products closely tied to consumers' relationships with their banks, while complaints related to credit cards and credit reporting do not increase. Finally, we find that the deposit rate response does not depend on whether the failed bank is acquired by an out-of-town bank or on the size of the ac-

quirer, suggesting that our findings are not driven by the identity of the acquiring bank or by a new acquirer introducing different deposit rates into the local market.

**Contribution to the literature.** This paper contributes to a large literature that examines the potential for bank runs ([Diamond and Dybvig 1983](#)). While the seminal focus was on bank fundamentals as the driver of depositor behavior, more recent work emphasizes that depositor actions are sensitive to information and beliefs, even when fundamentals are not fully deteriorated. For instance, studies have shown that depositors respond both to bank-specific news ([Chen, Goldstein, Huang, and Vashishtha 2022](#)) and to broader macroeconomic uncertainty ([Artavanis, Paravisini, Garcia, Seru, and Tsoutsoura 2022](#)), and moreover that local conditions matter ([Benmelech, Yang, and Zator 2023](#), [Maingi 2024](#), [Morelli, Moretti, and Venkateswaran 2025](#)). Historical episodes further demonstrate this behavior; [Blickle, Brunnermeier, and Luck \(2024\)](#) document that in 1930s Germany, depositors preemptively withdrew funds from both failing and ultimately surviving banks, suggesting that fears, rather than realized fundamentals, drove withdrawal behavior.<sup>1</sup> Long-run evidence indicates that bank failures are costly even when there is no evidence of fundamental triggers ([Jamilov, König, Müller, and Saidi 2024](#)). We link these non-fundamental spillovers through the local competition networks of banks.

On the bank side, research has shown that distressed banks raise deposit rates to attract or retain funding ([Martin, Puri, and Ufieri 2018](#)), and that banks also adjust deposit rates in response to heightened depositor attention even when fundamentals do not fully warrant such moves ([Chavaz and Slutzky 2024](#)). Our paper departs from much of this prior work by shifting the focus away from the failing bank itself. Instead, we study how the failure of a single bank affects the deposit market behavior of its local competi-

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<sup>1</sup>In the U.S. context, [Correia, Luck, and Verner \(2023\)](#) find that bank failures were highly predictable using publicly available accounting data, highlighting that some depositor movements could be grounded in fundamentals.

tors. By doing so, we shed new light on how the consequences of bank distress extend beyond the distressed institution to healthier nearby banks.

Because we interpret our results as a transition away from depositor sleepiness, our findings also contribute to the literature on deposit stickiness ([Hutchison and Pennacchi 1996](#), [Drechsler, Savov, and Schnabl 2017](#), [Egan, Hortaçsu, and Matvos 2017](#), [Xu, Song, and Zeng 2024](#), [Argyle, Iverson, Kotter, Nadauld, and Palmer 2025](#), [Cookson, Fox, Gil-Bazo, Imbet, and Schiller 2023](#), [Lu and Wu 2025](#), [Chen, Goldstein, Vashishtha, and Yin 2025](#), [Egan, Hortaçsu, Kaplan, Sunderam, and Yao 2025](#)). Sleepiness sustains deposit demand: households place non-rate convenience and liquidity value on an existing banking relationship and do not continuously reconsider it. Our findings suggest that a salient bank failure wakes depositors and dissipates that sleepiness, persistently shifting deposit demand inward. As such, we contribute to the literature on the drivers of variation in depositor stickiness ([Blickle, Li, Lu, and Ma 2025](#)). Moreover, our results suggest that the impacts of competitor bank failures can extend across lending types, given the synergies between the cost of deposit funding and lending outcomes ([Loutskina and Strahan 2009](#), [Li, Loutskina, and Strahan 2019](#), [Drechsler, Savov, and Schnabl 2021](#)).

Beyond the literature on liquidity transformation and depositor behavior, our paper also relates to the broader study of financial distress spillovers, particularly contagious bank runs (e.g., [Calomiris and Mason 1997](#)) as well as bank failures ([Goldstein, Kopytov, Shen, and Xiang 2024](#)). While earlier work has largely emphasized either (1) systemic or industry-wide spillovers or (2) spillovers to stock prices and funding outflows, we provide new evidence of geographically localized spillovers in a different domain: deposit rate setting. To our knowledge, we are the first to document that local competitor banks, even if fundamentally healthy, raise deposit rates following a nearby bank failure.

Our geographic focus also connects our paper to the literature on the local real effects of firm-level shocks (Shoag and Veuger 2018, Bernstein, Colonnelli, Giroud, and Iverson 2019, Benmelech, Bergman, Milanez, and Mukharlyamov 2019, Gathmann, Helm, and Schönberg 2020), which emphasizes the importance of local agglomerations.

Finally, our findings relate to macroeconomic studies on the broader consequences of banking instability (e.g., Gertler, Kiyotaki, and Prestipino 2017). While banking crises directly disrupt credit supply through bank failures, we highlight an additional channel: the longer-term adjustment in depositor behavior and bank pricing strategies induced by prior crises. Thus, the aftermath of a bank failure may shape the competitive environment and banks’ funding costs for an extended period, amplifying the economic costs of financial distress beyond the immediate fallout.

**Overview.** The rest of the paper is organized as follows. Section II describes the institutional background surrounding bank failures and our main datasets. Section III presents our empirical findings on how surviving banks in the local deposit market respond to a nearby bank failure. Section IV then presents a simple model of deposit competition that rationalizes these findings. Finally, Section V concludes by discussing the broader implications of our findings.

## II. Institutional Background and Data

### *A. Bank Failures*

When a bank fails, the main responsibilities of the FDIC are two-fold. First, the FDIC facilitates the bidding process with prospective bidders for acquiring the failed bank’s assets and deposits. Second, it protects insured depositors. During most of our sam-

ple, insured balances were protected up to \$100,000; the limit was temporarily raised to \$250,000 in October 2008 and made permanent in 2010. Importantly, as a part of this process, the attention of depositors was crucial for carrying out the FDIC’s role as deposit insurer, and thus the FDIC had to generate significant publicity around the bank failure event to ensure depositors are informed of the news.<sup>2</sup> Corroborating evidence of heightened public attention is presented in Appendix Figure A1, which shows that Google search volume for failed banks spikes dramatically around their failure. Moreover, Appendix Figure A2 shows that these search volume spikes are highly local, i.e., concentrated in the failed bank’s state. This local scope makes bank failures well suited for studying local spillovers.

To illustrate the broad geographic characterization of bank failures, panel A of Appendix Figure A3 shows counties with failed banks since 2006.<sup>3</sup> The figures illustrate two key patterns. First, bank failures are neither extremely rare nor extremely common; while bank failures occurred in a visually noticeable share of counties (around 9%), it is far from ubiquitous. Second, there is considerable variation among counties with bank failures, both in terms of geographic coverage and economic profile. These counties span nearly every region in the U.S. and include both urban and rural counties. We formally present the descriptive statistics of these counties later in the paper. These empirical features lend support for interpreting our findings on the effects of bank failures as representative and meaningful estimates.

As for aggregate time series trends, the top panel of Appendix Figure A4 presents the evolution of bank failures alongside deposit rates and the Federal Funds Rate from 1995 to 2025. The figure captures the main setting of our interest, the Global Financial Crisis.

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<sup>2</sup>“Every effort also is made to inform the public through the news media, town meetings, and notices posted at the bank.” (FDIC, <https://www.fdic.gov/bank-failures/when-bank-fails-facts-depositors-creditors-and-borrowers>)

<sup>3</sup>We focus on the sample of failed banks starting in 2006 because of the coverage of our bank branch deposit rate data. Panel B of Appendix Figure A3 shows counties with failed banks since 1934.

We observe that around 15% of system deposits were under some level of FDIC intervention during the height of the crisis, reflecting the significant concern about the solvency of the banking sector. Using Google search volume for FDIC as a proxy measure, the bottom panel of Appendix Figure A4 also demonstrates that depositor attention to bank failures spiked during the crisis. This heightened scrutiny, this paper argues, possibly dissipated the depositor sleepiness that sustains deposit demand at surviving banks. Importantly, we subsequently argue that this change in depositor demand can rationalize our empirical results presented later.

## *B. Data*

**FDIC data.** Our first dataset comes from the FDIC. Specifically, we use the FDIC’s bank failure data which lists each bank that received FDIC support since the 1930s. The data indicate the location of each bank’s headquarters along with other details related to the failure, including the acquirer of the failed bank and estimated cost incurred by the FDIC. We additionally obtain deposit quantity data at the bank branch-level, along with the location of each bank branch, from the FDIC Summary of Deposits (SOD).

**RateWatch.** We obtain our second main dataset from RateWatch, which provides branch-level advertised deposit rates by product type (e.g., money market accounts, certificates of deposit), amount, and maturity. In the main analysis, we focus on advertised 1-year CD rates for \$100,000, which offer broad and consistent reporting coverage in our sample.

**HMDA.** We use loan-level data from the Home Mortgage Disclosure Act (HMDA), focusing on first-lien, owner-occupied, 1-4 family home-purchase mortgages that were originated or purchased. We aggregate originated loan volume to county-year totals, separately measuring total, bank, and nonbank mortgage issuance. Bank and nonbank

lenders are classified based on agency codes.<sup>4</sup> For the bank-specific funding-exposure design, we link HMDA reporters to their contemporaneous bank using the Federal Reserve Bank of Philadelphia lender crosswalk and extend the outcome through 2023 to complete the post-failure event window.<sup>5</sup>

**Call Reports.** We obtain bank balance sheet data (e.g., total assets, deposits) at the quarterly level from U.S. Call Reports from the Federal Financial Institutions Examination Council (FFIEC).

**Google search data.** To measure the level of public attention around bank failures, we also manually collect the Google search volume for each failed bank’s name over time, as well as search volumes broken down by state. Because Google search indices are normalized and can be revised retrospectively, we interpret these measures as noisy proxies for relative salience around failure events.

**CFPB complaints data.** From the Consumer Financial Protection Bureau (CFPB), we also compile data on the volume of consumer complaints submitted to the CFPB over time, aggregated by state.

**Local economy.** Finally, to control for the time-varying effects of the local economy, we use unemployment rate, income per capita, and population, provided by the publicly available data from the Local Area Unemployment Statistics program of the Bureau of Labor Statistics. We obtain county-year-level house price growth data from Zillow. For robustness tests, we also use data on plant closure notices from Revelio Labs, and large-firm bankruptcy data from the Florida-UCLA-LoPucki Bankruptcy Research Database (BRD).

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<sup>4</sup><https://ffiec.cfpb.gov/documentation/faq/filing-faq>

<sup>5</sup><https://www.philadelphiafed.org/surveys-and-data/consumer-finance-data/home-mortgage-disclosure-act-lender-file>

### *C. Summary Statistics*

The combined dataset spans the years between 2004 and 2021. Our identifying variation comes almost entirely from the 2008–2013 failure wave surrounding the Global Financial Crisis, which accounts for roughly 95 percent of treated first-failure events; our estimates should therefore be interpreted as characterizing deposit market spillovers during this crisis period.

Appendix Table A1 presents the summary statistics for our sample period, which contains 543 failures. Our paper focuses on the half of bank failures with the highest resolution costs; for our proposed spillover channel of bank failures, the failure event has to be significant enough (e.g., to generate local publicity).<sup>6</sup> Panel A shows that their average estimated cost to the FDIC is \$249 million, while the average failed bank holds \$944 million in deposits.

Panel B of Appendix Table A1 presents branch-level summary statistics for the main outcome variable in our paper. Specifically, it shows that deposit rates are low during our sample period; the average 1-year CD rates are 0.378% for \$100,000 deposits and 0.376% for \$500,000 deposits. Nevertheless, there is significant geographic variation in deposit rates, as illustrated in Appendix Figure A5. Additionally, the average bank branch holds around \$118 million in deposits.

Finally, panel C of Appendix Table A1 compares counties with high-cost failures to counties without high-cost failures. It shows that the average county with a high-cost failure is notably larger than the average comparison county in terms of population (524,325 versus 71,103), although the distribution is wide and includes many smaller local banking markets as well. Accordingly, treated counties also have more banks and

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<sup>6</sup>When we instead define treatment using all bank failures, our main estimated effect is smaller but remains statistically significant (presented in Section III).

bank branches on average. As a result of these county size differences, our empirical specifications account for size, specifically population, and later robustness exercises address concerns related to size differences. On average, treated counties have slightly higher unemployment rates, but also higher house price growth and income per capita. We include county fixed effects and county-year-level control variables in the empirical exercises below.

### III. Empirical Analysis

#### *A. Deposit Market Spillovers*

In this section, we evaluate the effect of bank failures on local competitor banks' deposit rates and deposit quantities. To estimate these spillover effects, we regress  $r_{ibct}$ , the deposit rate at bank  $b$ 's branch  $i$  in county  $c$  in year  $t$ , on the treatment variable  $Bank\ Failed_{ct}$ , which indicates whether a bank had failed in county  $c$  as of year  $t$ . We only flag the county that houses the failed bank's headquarters, where its local presence and footprint would be most significant. We also only flag the first bank failure in a county during our sample period; subsequent failures in the same county are not coded as separate events. Importantly, in addition to county-level controls  $X_{ct}$  (e.g., unemployment rate, house price growth), our specification includes bank-year fixed effects  $\alpha_{bt}$ . This term therefore captures the effect of unobservable bank-year-specific fundamentals on deposit rates (e.g., credit demand across their lending network), and we can isolate the remaining variation attributable to differences across branches within a bank-year. The formal regression specification is written as

$$r_{ibct} = \beta Bank\ Failed_{ct} + \gamma X_{ct} + \alpha_{bt} + \alpha_c + \varepsilon_{ibct}. \quad (1)$$

The coefficient of interest,  $\beta$ , captures the effect of bank failures on deposit rates of branches in the same county. Our identifying assumption is parallel trends; i.e., deposit rates in our sample counties' bank branches would have followed parallel trends absent bank failures. If our assumption holds, we can interpret any differences in deposit rates as attributable to bank failures.

In all of our specifications, we also drop counties with an average population above three million (the five most populous counties), weight each observation by county population, and cluster standard errors at the county-level. We also exclude the failed bank's local branches and the branches of acquiring banks, to ensure that we are capturing the response of surviving banks unrelated to the failed-bank transfer. Finally, to mitigate concerns about sample attrition and changes to RateWatch coverage, we exclude branches that enter RateWatch in or after the failure year or exit before it.

### A.1. Deposit Rates

In Table 1, we report the results from estimating Equation (1) using deposit rates of 1-year \$100,000 CDs as the outcome variable.<sup>7</sup> Across all columns, the estimates for *Bank Failed* are strongly statistically significant. In column 3, our preferred specification that controls for county-level economic conditions, the coefficient on *Bank Failed* is statistically significant at the 0.1% level. This effect is also economically significant. Column 3 implies that a bank failure is associated with a 3.44 basis-point increase in the 1-year rate for \$100,000 CDs, approximately 9 percent of the branch-level sample mean. As an alternative benchmark, this magnitude is about 57 percent of the average within-bank-

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<sup>7</sup>Appendix Table A2 presents a version that includes bank fixed effects and year fixed effects instead of bank-year fixed effects. While the point estimates for *Bank Failed* are positive, they are statistically insignificant. The results change notably with the inclusion of bank-year fixed effects. First, the R-squared increases dramatically, from 0.80 and 0.86 to 0.98 and 0.99, respectively. This is consistent with the findings in [Begenau and Stafford \(2023\)](#), who document that bank-wide uniform pricing decisions account for most of the variation in deposit rates. More importantly, the coefficients become strongly statistically significant, indicating that the inclusion of bank-year fixed effects is crucial for our empirical design.

**Table 1: Bank Failures and Deposit Rates**

The table reports the results from estimating Equation (1), which examines the effect of a bank failure on local competitors' deposit rates. The dependent variable is the 1-year CD rate for a \$100K deposit, measured in basis points. The sample excludes the failed bank's local branch footprint and all branches of acquiring banks. Bank Failed is an indicator for a bank failure in a county-year. Standard errors are clustered at the county level and reported in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                    | $r_{100K}$        |                   |                    |
|--------------------|-------------------|-------------------|--------------------|
|                    | (1)               | (2)               | (3)                |
| Bank Failed        | 2.96***<br>(1.00) | 5.49***<br>(1.18) | 3.44***<br>(1.00)  |
| Unemployment Rate  |                   |                   | 0.85***<br>(0.21)  |
| Income/Capita      |                   |                   | -0.00***<br>(0.00) |
| Income Growth      |                   |                   | 0.54<br>(3.04)     |
| House Price Growth |                   |                   | -2.56<br>(2.39)    |
| Bank-Year FE       | Yes               | Yes               | Yes                |
| County FE          | Yes               | Yes               | Yes                |
| County Controls    | No                | No                | Yes                |
| Weights            | None              | County Pop.       | County Pop.        |
| Num. obs.          | 321960            | 321960            | 297031             |
| R <sup>2</sup>     | 0.98              | 0.99              | 0.99               |

year standard deviation in deposit rates across branches. Thus, relative to the limited variation that remains within a bank-year, the effect of a local bank failure on deposit rates is substantial.

**Robustness.** We first conduct robustness tests to address concerns about size differences between failure and control counties, which we noted in the summary statistics in Section II. First, our baseline results could be driven by small, low-population counties in the control group. As a simple test, we re-estimate Equation (1) after excluding counties with populations below 250,000, which results in treated and control counties with roughly similar average populations. Appendix Table A3 shows that the resulting estimates are essentially unchanged, suggesting that these effects are unlikely to be explained by differences in county population.

We next take a more systematic matching approach. Appendix Table A4 re-estimates the baseline using a stacked design in which each failure county is compared with never-treated counties matched on the pre-failure path of observable local fundamentals within the same event window. This procedure substantially reduces differences in observable characteristics between treated and control counties. Moreover, because each stack draws its controls only from never-treated counties within a common event window, counties treated at other dates cannot serve as controls, avoiding the weighting problems that can arise when already-treated units enter the comparison group in staggered designs (Sun and Abraham 2021, Callaway and Sant’Anna 2021). The resulting estimates remain positive and statistically significant, providing further evidence that differences between failure and control counties are unlikely to explain our findings.

Next, we address the concern that bank failures are endogenous to local economic conditions. Specifically, bank failures are not random events and may occur in areas experiencing particularly severe economic downturns. If so, our estimates could reflect banks’ deposit rate responses to broader local economic distress rather than to the bank failure itself. To examine this possibility, we conduct placebo tests using two other salient local adverse events: large plant closures and large firm bankruptcies. Like bank failures, these events may signal a local recession, but unlike bank failures, they do not directly concern banks or how depositors think about their deposit accounts with banks. Appendix Table A5 shows that neither event is associated with deposit rates in the same sample, suggesting that our findings are unlikely to reflect a generic response to local recessions.

As an additional test, we include state-year fixed effects in our baseline specification to absorb broader state-level shocks that could simultaneously contribute to bank failures and changes in deposit rates. Appendix Table A6 shows that the resulting estimate

is smaller but remains positive and statistically significant. Taken together, these tests suggest that broader local and state economic conditions are unlikely to fully explain the association between deposit rates and bank failures.

**Heterogeneity.** We first test whether the size of the failed bank’s local footprint matters for the deposit rate response. This is closely related to our initial hypothesis that the scale of bank failure is crucial for generating an effect, which subsequently motivated our focus on the half of bank failures with the highest resolution costs.<sup>8</sup> Appendix Table A8 allows our baseline estimate to vary with the failed bank’s pre-failure local deposit share and branch share. Along both dimensions, we find that failures with larger local footprints indeed generate stronger effects.

An additional heterogeneity analysis to assess the validity of our empirical design, Appendix Table A9 examines heterogeneity among surviving banks based on their pre-failure dispersion in advertised rates across branches. Naturally, we would expect our design to be most informative for banks that historically set different rates across local markets. Consistent with this prediction, banks with greater pre-failure rate dispersion exhibit substantially larger responses to a neighboring bank failure.

Appendix Table A10 documents geographic heterogeneity, with the largest responses to bank failures in the Northeast and West. This pattern, combined with evidence of coastal counties offering lower rates (Appendix Figure A5), may reflect that these regions have greater scope for the depositor-attention mechanism emphasized in the paper.

We also examine the geographic scope of the deposit rate response. Appendix Table A11 considers alternative definitions of treated branches by their distance from the failed bank’s headquarters. The estimated effect is largest within 20 miles of the failed

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<sup>8</sup>Appendix Table A7 shows that when we expand the treatment definition to include all bank failures, the estimated effects are smaller but remain statistically significant.

bank’s headquarters (a radius that roughly corresponds to the failure county), remains sizable but smaller between 20 and 40 miles, and becomes dramatically smaller and statistically indistinguishable from zero between 40 and 80 miles. This pattern is consistent with the local nature of the spillovers emphasized in our empirical design.

**Uninsured deposits.** Next, to better understand the mechanism behind the deposit rate response to bank failures, we compare the effect across insured and uninsured deposits. Deposits of \$100,000 or less are fully insured under FDIC coverage, while deposits of \$500,000 are not. If depositors’ concerns about the risk of losing their deposits were the primary driver of rate increases – an intuitive explanation, since a nearby bank failure could lead to depositors updating their beliefs about the safety of their own bank – we would expect a larger effect for uninsured deposits. Table 2 reports the effect of bank failures on \$500K CD rates, using the same structure as Table 1. Surprisingly, we find that deposit rates in fact rise by less for uninsured deposits following a bank failure. The coefficient in the final column, our preferred specification, implies an effect that is only about half as large as the effect we find for the \$100K CD rate. This evidence points against a pure risk-based explanation and is instead more consistent with a broader failure-induced dissipation of depositor sleepiness, resulting in a reduction of the non-rate value they place on deposits.

**Dynamics.** Figure 1 reports the dynamic effects of a bank failure on local competitors’ deposit rates for both insured and uninsured CDs. First, the estimates at  $t = -2$  are statistically insignificant in both panels relative to the omitted year  $t = -1$ , suggestive of no differential pre-trends.<sup>9</sup> The insured \$100,000 CD rate rises immediately and remains elevated through  $t = 3$ ; all post-period coefficients are statistically significant. The uninsured \$500,000 CD response is positive at every post-failure horizon, although statistical

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<sup>9</sup>Due to our data availability, event-time estimates at leads earlier than  $t = -2$  are identified from a very small subset of treated counties (e.g., a balanced window extending to  $t = -6$  contains a single treated county).

**Table 2: Bank Failures and Deposit Rates: Uninsured Deposits**

The table reports the results from estimating Equation (1), which examines the effect of a bank failure on local competitors' deposit rates. The dependent variable is the 1-year CD rate for a \$500K deposit, measured in basis points. The sample excludes the failed bank's local branch footprint and all branches of acquiring banks. Bank Failed is an indicator for a bank failure in a county-year. Controls include local unemployment, income per capita, income growth, and house price growth. Standard errors are clustered at the county level and reported in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                 | $r_{500K}$        |                   |                   |
|-----------------|-------------------|-------------------|-------------------|
|                 | (1)               | (2)               | (3)               |
| Bank Failed     | 2.25***<br>(0.76) | 3.76***<br>(0.84) | 2.05***<br>(0.61) |
| Bank-Year FE    | Yes               | Yes               | Yes               |
| County FE       | Yes               | Yes               | Yes               |
| County Controls | No                | No                | Yes               |
| Weights         | None              | County Pop.       | County Pop.       |
| Num. obs.       | 321960            | 321960            | 297031            |
| R <sup>2</sup>  | 0.98              | 0.99              | 0.99              |

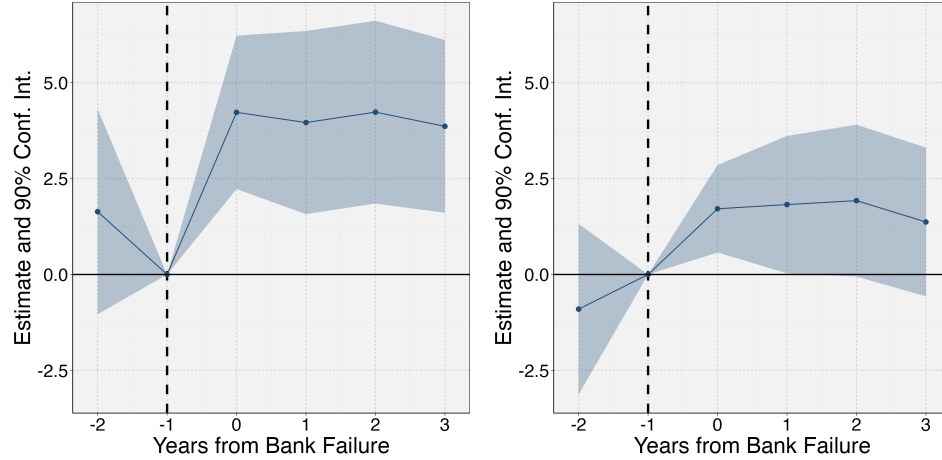
significance varies; the coefficients for  $t = 2$  and  $t = 3$  are marginally insignificant. Appendix Figure A6 reports the corresponding event-time estimates using the estimator of Sun and Abraham (2021), which reveal broadly the same patterns.

**External validity.** Next, we examine the scope and external validity of our deposit rate results. First, Appendix Table A12 extends the analysis across nine different products in RateWatch. The coefficients are positive and statistically significant across CD products, but not for savings and checking accounts. This distinction is consistent with CDs being the primary products through which banks actively compete on deposit rates during our sample period.

We next examine which branches drive the response. Appendix Table A13 shows that when we broaden the sample from branches that consistently report both \$100K and \$500K CD rates to branches that report both products in or after the failure year, the estimated effect becomes smaller, although it remains statistically significant. The effect weakens considerably further and becomes statistically insignificant when we instead

**Figure 1: Bank Failures and Deposit Rate Dynamics**

This figure shows the dynamic effect of a bank failure on local deposit rates. The left panel uses the 1-year \$100,000 CD rate and the right panel uses the 1-year \$500,000 CD rate. All regressions include county fixed effects and bank-year fixed effects, and additionally control for unemployment rate, income per capita, income growth, and house price growth. Standard errors are clustered at the county-level and observations are weighted by county population. The blue shaded area denotes the 90% confidence interval.



focus on branches that report \$100K but not \$500K CD rates. These results suggest that the pricing response is concentrated among branches positioned to compete actively for large CDs. Accordingly, our analysis is intended to capture such branches, rather than to represent all deposit-taking branches, and therefore focuses on branches that quote both products.

The deposit rate response also varies across failure cohorts. Appendix Table [A14](#) splits the baseline sample by failure cohort while retaining the same control counties. The response is positive and strongly statistically significant for failures through 2011, but statistically insignificant for failures from 2012 onward. Thus, our deposit rate results primarily characterize bank failures occurring during the crisis period and may not generalize to failures occurring under more normal financial conditions.

These results help delineate the scope of our deposit rate findings and offer appropriate caveats about extrapolation. The quantity evidence in the following section, however, is considerably broader: deposit growth declines not only among the branches

underlying our deposit rate results, but also across the full universe of branches in the SOD.

### *A.2. Deposit Growth*

Rates alone cannot distinguish an inward shift in deposit demand from an increase in banks' demand for funding; deposit quantities help make this distinction. If stronger bank demand for funding were the primitive force behind higher rates, deposits should increase. If a bank failure instead reduces households' willingness to hold local bank deposits, banks could raise rates and still lose deposits. Therefore, to distinguish between these explanations, we examine the response of annual branch deposit growth to bank failures.

Our main specification in this section follows the preceding analysis and compares branches of the same bank located in counties with and without a local failure. Table 3 reports the effect of bank failures on survivors' deposit growth using the full SOD branch sample. Our preferred specification (column 2) reports a coefficient of -2.45, indicating that deposit growth decline after a nearby bank failure is substantial and broad. Appendix Table A15 estimates the same specification using the exact branch sample underlying our baseline deposit rate results. For these branches, deposit growth falls by an even larger 4.18 percentage points, suggesting that even branches raising deposit rates following a nearby failure experience slower deposit growth.

Figure 2 shows the corresponding dynamic estimates. The pattern mirrors the deposit rate dynamics, but in the opposite direction. Specifically, the pre-period coefficient is close to zero, while deposit growth falls sharply in the failure year and remains persistently lower in subsequent years.

**Table 3: Bank Failures and Deposit Growth**

This table reports the effect of a bank failure on local deposit growth at the branch-year level. The dependent variable is annual log branch deposit growth, measured in percentage points. The sample is the full SOD branch sample, excluding branches of the failed bank. Controls include local unemployment, income per capita, income growth, and house price growth. Standard errors are clustered at the county-level and reported in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                 | (1)                | (2)                |
|-----------------|--------------------|--------------------|
| Bank Failed     | -2.35***<br>(0.70) | -2.45***<br>(0.73) |
| Bank-Year FE    | Yes                | Yes                |
| County FE       | Yes                | Yes                |
| County Controls | No                 | Yes                |
| Weights         | County Pop.        | County Pop.        |
| Num. obs.       | 1074068            | 890650             |
| R <sup>2</sup>  | 0.21               | 0.21               |

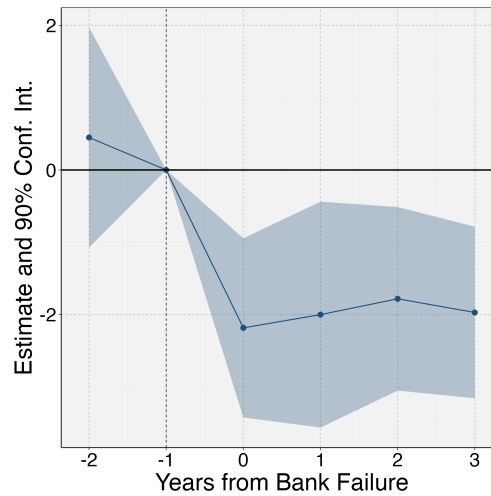
We next aggregate deposits to the county-level. Unlike the branch-level analysis, which excludes the failed bank to isolate the response of surviving competitors, the county-level analysis captures deposits across all local branches, including those of the failed bank following its acquisition. This distinction is important because an acquiring bank could retain or attract deposits at the former failed bank branches, potentially offsetting the decline in deposit growth among surviving competitors. Table 4 shows that this is not the case: county-level deposit growth declines significantly by 3.36 percentage points following a bank failure.<sup>10</sup> Thus, the decline in deposit growth among surviving branches is not offset by deposit growth elsewhere in the local banking market, providing further evidence of an inward shift in local deposit demand.

The aggregate decline in local deposit growth raises a natural question: where does the money go? If a salient bank failure “wakes up” otherwise sleepy depositors, the resulting reallocation need not stop at switching banks; depositors may broadly move funds out of low-yielding bank deposits and toward higher-yielding financial assets. Table 5 examines whether the decline in deposit growth is accompanied by a shift toward

<sup>10</sup> Appendix Figure A7 reports the corresponding dynamic estimates, which show that the dynamic pattern of the county-level deposit growth decline is similar to the pattern observed at the branch-level for survivor banks.

**Figure 2: Bank Failures and Branch Deposit Growth Dynamics**

This figure shows the dynamic effect of a local bank failure on annual branch deposit growth in the balanced full SOD branch sample, excluding branches of the failed bank. The regression includes county fixed effects, bank-year fixed effects, and controls for local unemployment, income per capita, income growth, and house price growth. Standard errors are clustered at the county level and observations are weighted by county population. The blue shaded area denotes the 90% confidence interval.



alternative financial assets, using IRS taxable interest income scaled by county deposits and dividend income scaled by adjusted gross income (AGI).

The table shows that interest income per dollar of local deposits rises by 0.73 percentage points following a bank failure, roughly half the median. Thus, even as local deposits decline, taxable interest income received by county residents does not decline with them. This pattern suggests that balances leaving the local deposit system continue to earn interest elsewhere, consistent with households reallocating funds toward non-deposit or out-of-county interest-bearing assets. The second column reveals a similar message using IRS dividend income scaled by AGI. Because money market fund distributions are generally reported as dividends rather than interest, this measure provides a useful county-level proxy for shifts toward money market funds and related non-deposit assets. We find that dividend income rises by 0.26 percentage points relative to AGI following a bank failure.

**Table 4: Bank Failures and Deposit Growth: County-level**

This table reports the effect of a bank failure on local deposit growth at the county-year level. County deposits are aggregated across all branches in the full FDIC Summary of Deposits. Controls include local unemployment, income per capita, income growth, and house price growth. Standard errors are clustered at the county-level and reported in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                 | (1)                | (2)                |
|-----------------|--------------------|--------------------|
| Bank Failed     | -3.17***<br>(0.87) | -3.36***<br>(0.92) |
| County FE       | Yes                | Yes                |
| Year FE         | Yes                | Yes                |
| County Controls | No                 | Yes                |
| Weights         | County Pop.        | County Pop.        |
| Num. obs.       | 64135              | 41941              |
| R <sup>2</sup>  | 0.33               | 0.31               |

Taken together, these results paint a consistent picture: deposits leave the local banking system, but the funds do not simply disappear from households' financial portfolios. Instead, they appear to remain invested in interest-bearing assets, with the increase in dividend income particularly consistent with reallocation toward money market funds and related non-deposit alternatives. While the IRS data do not allow us to directly identify the destination of these funds, the evidence provides an important link between the decline in local deposits and households' broader portfolio reallocation. Moreover, this finding is consistent with sleepy depositors becoming more attentive to their savings following a bank failure and reallocating funds toward higher-yielding alternatives.

### *B. Loan Market Spillovers*

Having established the effect of nearby bank failures on the liabilities of surviving banks, we next turn to local credit provision. We use HMDA data on mortgage originations, aggregating home-purchase mortgage volume to the county-year level. We focus on bank mortgage originations and banks' share of total mortgage originations as our outcome variables. These outcomes allow us to examine whether bank lending contracts

**Table 5: Bank Failures and Where Deposits Go**

This table reports county-year regressions of IRS income measures on Bank Failed. The outcomes are taxable interest income divided by county deposits (column 1, percentage points) and dividend income divided by adjusted gross income (column 2, percentage points). County deposits are aggregated from the full FDIC Summary of Deposits. All columns use the same county-year sample. Controls include local unemployment, income per capita, income growth, and house price growth. Standard errors are clustered at the county level and reported in parentheses. \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

|                 | Int./Dep.<br>(1) | Div./AGI<br>(2)   |
|-----------------|------------------|-------------------|
| Bank Failed     | 0.73**<br>(0.35) | 0.26***<br>(0.09) |
| County FE       | Yes              | Yes               |
| Year FE         | Yes              | Yes               |
| County Controls | Yes              | Yes               |
| Weights         | County Pop.      | County Pop.       |
| Num. obs.       | 34767            | 34767             |
| R <sup>2</sup>  | 0.17             | 0.85              |

following a nearby failure and whether the composition of local mortgage credit shifts away from banks.

We estimate county-year regressions of bank mortgage issuance and the bank share of issuance on local bank failures, formally written as:

$$Y_{ct} = \beta \text{Bank Failed}_{ct} + \gamma X_{ct} + \alpha_c + \alpha_t + \varepsilon_{ct}. \quad (2)$$

$Y_{ct}$  denotes either the log volume of bank mortgage originations or banks' share of total mortgage originations in county  $c$  and year  $t$ . We use a common sample of county-years with positive mortgage originations by both banks and nonbanks. The remaining terms follow Equation (1), with  $X_{ct}$  including local unemployment, income per capita, income growth, and house price growth.

Table 6 reports the results.<sup>11</sup> We find that local bank lending declines significantly following a bank failure. Specifically, bank mortgage originations fall by 7.3 log points. By contrast, nonbank originations are not affected by bank failures, and therefore banks'

<sup>11</sup> Appendix Figure A8 reports the corresponding dynamics.

**Table 6: Bank Failures, Bank Mortgage Issuance, and Bank Share**

This table reports county-year regressions on Bank Failed, an indicator for whether a bank failed in a county-year. The dependent variables are log bank HMDA mortgage origination volume (column 1), log nonbank HMDA mortgage origination volume (column 2), log total HMDA mortgage origination volume (column 3), and the bank share of HMDA mortgage origination volume in percentage points (column 4). All outcomes use the same county-year sample, which requires positive issuance by both bank and nonbank lenders. Controls include local unemployment, income per capita, income growth, and house price growth. Standard errors are clustered at the county level and reported in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                 | Bank Issuance     | Non-Bank Issuance | Total Issuance  | Bank Share        |
|-----------------|-------------------|-------------------|-----------------|-------------------|
|                 | (1)               | (2)               | (3)             | (4)               |
| Bank Failed     | -0.07**<br>(0.03) | -0.00<br>(0.03)   | -0.04<br>(0.03) | -1.90**<br>(0.80) |
| County FE       | Yes               | Yes               | Yes             | Yes               |
| Year FE         | Yes               | Yes               | Yes             | Yes               |
| County Controls | Yes               | Yes               | Yes             | Yes               |
| Weights         | County Pop.       | County Pop.       | County Pop.     | County Pop.       |
| Num. obs.       | 30998             | 30998             | 30998           | 30998             |
| R <sup>2</sup>  | 0.99              | 0.98              | 0.99            | 0.90              |

share of total mortgage originations falls by 1.90 percentage points. The resulting total decline across all lenders is 4.1 log points, although this estimate is statistically insignificant.

One interpretation of the above findings is a contraction in bank lending and a resulting shift in the composition of local mortgage credit away from banks. Nonbank lenders appear unable to absorb this decline. However, these results alone cannot rule out a lender-specific shift in borrower demand. For example, borrowers may become less willing to obtain mortgages from banks following a nearby failure, even when nonbank alternatives are limited. We therefore use the newly linked HMDA panel to test whether the decline in lending is concentrated among surviving banks whose funding was more exposed to the failure county before the event.

For each surviving bank, we define *Funding Exposure* as the share of the bank's total Summary of Deposits balances located in the failure county in the year before failure. Because the distribution of funding exposure is strongly right-skewed, we define *High Funding Exposure* as an indicator for bank-county pairs in the top quartile of funding

exposure (above 15.5 percent) among treated bank-county pairs in the mortgage estimation sample. Formally, we estimate

$$Y_{bct} = \beta \left( \text{Bank Failed}_{ct} \times \text{High Funding Exposure}_{bc} \right) + \alpha_{bc} + \alpha_{bt} + \alpha_{ct} + \varepsilon_{bct}, \quad (3)$$

where  $\alpha_{bc}$  denotes bank-county fixed effects,  $\alpha_{bt}$  bank-year fixed effects, and  $\alpha_{ct}$  county-year fixed effects. The county-year fixed effects absorb common local mortgage-demand shocks, while bank-year fixed effects absorb changes in a bank's overall lending. Identification therefore comes from comparing banks with different predetermined funding exposure to the failure county within the same county-year. If the decline in mortgage lending reflects a contraction in credit supply stemming from local funding pressure, banks with greater pre-failure funding exposure should reduce lending more. As in the preceding analysis, we exclude failed and acquiring banks. Because mortgage originations can be zero, we estimate the specification using Poisson pseudo-maximum likelihood (PPML).

Table 7 reports the results.<sup>12</sup> According to our PPML estimates in our preferred specification (column 2), mortgage originations at high-exposure banks decline by 20.9 percent after a bank failure. These estimates are statistically significant at the 1 percent level. Because the specification absorbs common county-level mortgage-demand shocks and bank-wide lending changes, this pattern provides further evidence consistent with a local credit-supply contraction stemming from funding exposure.

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<sup>12</sup>Appendix Figure A9 reports the corresponding dynamics.

**Table 7: High Funding Exposure and Mortgage Lending**

This table reports bank-county-year PPML regressions of HMDA mortgage origination volume on Bank Failed interacted with High Funding Exposure. Funding Exposure is the failure county's share of the bank's total deposits in the year before failure. High Funding Exposure identifies the top quartile of treated bank-county pairs in the mortgage estimation sample. Both columns include zero originations for HMDA-reporting bank-years. Column 1 is unweighted, and column 2 is weighted by county population. All specifications include bank-county, bank-year, and county-year fixed effects. Failed and acquiring banks are excluded. Standard errors are two-way clustered by county and bank. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                                            | (1)                  | (2)                  |
|--------------------------------------------|----------------------|----------------------|
| Bank Failed $\times$ High Funding Exposure | -0.173***<br>(0.055) | -0.235***<br>(0.086) |
| Bank-County FE                             | Yes                  | Yes                  |
| Bank-Year FE                               | Yes                  | Yes                  |
| County-Year FE                             | Yes                  | Yes                  |
| Weights                                    | None                 | County Pop.          |
| Num. obs.                                  | 180,825              | 180,825              |

### *C. Mechanism Analysis*

The results thus far indicate that bank failures cause sustained deposit rate increases alongside weaker deposit growth, a decline in bank mortgage issuance, and a lower bank share of local mortgage originations. We interpret this joint pattern as an inward shift in deposit demand caused by a failure-induced dissipation of depositor sleepiness. This section further examines the mechanism. We first test the trigger: whether consumers become more attentive after a failure, using consumer complaints data. We then examine which surviving banks respond, using pre-failure bank and acquirer characteristics to distinguish this deposit-demand interpretation from risk-compensation and market-structure explanations.

**Consumer complaints.** To learn more about the role of depositor attention, we turn to data on consumer complaints from the Consumer Financial Protection Bureau (CFPB). Complaints provide a distinct and potentially informative measure of depositor behavior, particularly their attention. More specifically, filing a complaint requires awareness

and active engagement with one's bank, and therefore provides a useful measure of whether depositors become more attentive following a nearby bank failure.

For the formal analysis, we aggregate CFPB complaints into a bank-state-year panel. We conduct the analysis at the state level because complaints are relatively sparse at the bank-county-year level. For each state, we define the failure year as the first year in which a county in our baseline sample experiences a bank failure, and use the same  $[-2, +3]$  event window as in our baseline analysis. Because complaints are count outcomes and many bank-state-year observations have zero complaints, we estimate the specification using PPML. We include bank-by-year fixed effects and state fixed effects. Thus, the specification compares complaints against the same bank in the same year across states with different exposure to bank failures, while accounting for permanent differences across states.

Table 8 reports the results. Overall complaint activity increases by approximately 11 percent following a bank failure; the sample mean is 0.79 complaints per bank-state-year. More importantly, the table allows us to examine which types of complaints account for this increase. We separately consider complaints related to deposit accounts, mortgages, credit cards, and credit reporting.<sup>13</sup> Deposit account complaints increase significantly following a bank failure, while complaints related to credit cards and credit reporting, which are theoretically less connected to depositors' banking relationships, do not. Mortgage complaints also increase. This result is consistent with the same interpretation, as mortgages represent another important relationship between consumers and their banks. The sharp differences across complaint categories provide particularly informative evidence on the attention mechanism: the increase in complaints is concentrated precisely in the financial products for which greater attention to one's banking

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<sup>13</sup>Appendix Table A16 restricts the four category-specific regressions to a common estimation sample. Appendix Figure A10 reports the corresponding dynamics for deposit account complaints.

**Table 8: Bank Failures and CFPB Complaints**

This table reports the effect of the first bank failure in a state on CFPB complaint activity in a bank-state-year panel, estimated by PPML on the complaint count. A state's failure year is the first failure year among the treated counties in the baseline sample. The specification includes bank-by-year fixed effects and state fixed effects. Standard errors are clustered at the state level and reported in parentheses. \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

|                             | All complaints     | Deposit accounts   | Mortgages         | Credit cards    | Credit reporting |
|-----------------------------|--------------------|--------------------|-------------------|-----------------|------------------|
|                             | (1)                | (2)                | (3)               | (4)             | (5)              |
| First Bank Failure in State | 0.11 ***<br>(0.03) | 0.12 ***<br>(0.04) | 0.11 **<br>(0.04) | -0.02<br>(0.03) | 0.06<br>(0.17)   |
| State FE                    | Yes                | Yes                | Yes               | Yes             | Yes              |
| Bank-Year FE                | Yes                | Yes                | Yes               | Yes             | Yes              |
| Num. obs.                   | 192262             | 20882              | 44420             | 17812           | 43288            |
| Pseudo R <sup>2</sup>       | 0.83               | 0.69               | 0.85              | 0.86            | 0.96             |

relationship should matter most. Taken together, these results are difficult to reconcile with a broad increase in consumer dissatisfaction or a broad deterioration of financial firms' practices following a local bank failure. Instead, they provide further evidence that bank failures increase depositor attention and engagement.

**Bank characteristics.** We next examine how the deposit rate response varies across surviving banks. These tests also provide additional evidence on whether higher deposit rates reflect greater concerns about bank risk. Importantly, Section III documented a weaker response for uninsured deposits, even though these depositors are more exposed to losses in the event of a bank failure. We now examine the role of risk premium from a different perspective by testing whether the response is stronger among surviving banks that themselves appear more vulnerable. In particular, if a nearby bank failure causes depositors to become more concerned about the safety of their own bank, we would expect weakly capitalized banks to raise deposit rates more.

We begin by examining differences in banks' pre-existing capitalization. We define  $Low\ Capital_{bc}$  as an indicator equal to one if bank  $b$  was in the bottom tercile of the equity-to-assets distribution in the year immediately before the failure in county  $c$ . Formally,

**Table 9: Bank Characteristics, Failure, and Deposit Rates**

This table reports heterogeneity in the effect of bank failures on \$100K deposit rates by pre-existing bank characteristics. Columns 1–3 separately interact Bank Failed with Low Capital, Small Bank, and Low Net Loan Share, respectively. Each indicator equals one when the bank is in the bottom tercile of the relevant characteristic’s cross-sectional distribution in the calendar year immediately before the local failure, and the classification is held fixed throughout the event window. Column 4 includes all three interactions in a saturated specification. Standard errors are clustered at the county level and reported in parentheses. \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

|                                  | (1)               | (2)                | (3)              | (4)                |
|----------------------------------|-------------------|--------------------|------------------|--------------------|
| Bank Failed                      | 5.46***<br>(1.79) | 3.45***<br>(1.00)  | -0.32<br>(1.08)  | 2.02**<br>(0.97)   |
| Bank Failed x Low Capital        | -7.25**<br>(2.88) |                    |                  | -4.76***<br>(1.23) |
| Bank Failed x Small Bank         |                   | -2.59***<br>(1.00) |                  | -1.35<br>(2.04)    |
| Bank Failed x Low Net Loan Share |                   |                    | 7.05**<br>(2.92) | 5.14***<br>(1.74)  |
| County FE                        | Yes               | Yes                | Yes              | Yes                |
| Bank-Year FE                     | Yes               | Yes                | Yes              | Yes                |
| County Controls                  | Yes               | Yes                | Yes              | Yes                |
| Weights                          | County Pop.       | County Pop.        | County Pop.      | County Pop.        |
| Num. obs.                        | 297023            | 297023             | 297023           | 297023             |
| R <sup>2</sup>                   | 0.99              | 0.99               | 0.99             | 0.99               |

we estimate the following specification:

$$r_{ibct} = \delta \cdot \text{Bank Failed}_{ct} + \beta \cdot (\text{Bank Failed}_{ct} \times \text{Low Capital}_{bc}) + \gamma X_{ct} + \alpha_{bt} + \alpha_c + \varepsilon_{ibct}. \quad (4)$$

Table 9 reports the results. Column 1 shows that banks in the upper two capitalization terciles raise deposit rates by 5.46 basis points following a nearby failure. In contrast, the interaction for banks in the bottom capitalization tercile is -7.25 basis points, implying, in fact, a rate *decrease* for these banks. This pattern runs directly counter to the risk-premium explanation: if depositors were demanding greater compensation for perceived bank risk, we would expect precisely these weakly capitalized banks to face greater pressure to raise rates, rather than the opposite.

The remaining columns provide additional evidence on which banks are able to respond. Column 2 shows that banks in the upper two size terciles raise rates by 3.45 basis points, while the response is 2.59 basis points smaller among banks in the bottom size tercile. Column 3 shows an especially strong response among banks with relatively low loan-to-asset ratios: the response among banks outside the bottom loan-share tercile is close to zero, while the low-loan-share interaction is 7.05 basis points. Appendix Table A17 reports the corresponding \$500K results and shows the same qualitative pattern.

Taken together, these results reinforce the interpretation from our earlier comparison of insured and uninsured deposits. The deposit rate response does not appear to be concentrated where a risk-premium explanation would predict: among uninsured deposits or at the weakest-capitalized banks. This pattern is more consistent with surviving banks broadly facing pressure to retain deposits following a local bank failure, but differing in their ability to respond by offering higher rates.

**Acquirer characteristics.** Another potential explanation for our deposit rate results is that they are driven by the acquiring bank rather than the bank failure itself. When a failed bank is acquired, the acquirer may introduce a different deposit pricing policy into the local market. This possibility may be particularly relevant when the acquirer did not previously operate in the county, since an out-of-town bank could bring substantially different deposit rates into the local market and affect the pricing decisions of surviving competitors. If this channel explains our findings, we would expect the deposit rate response to depend on the characteristics of the acquiring bank.

To examine this possibility, we identify the acquiring bank using the FDIC failed bank list and Summary of Deposits branch records. For each failed bank, we locate its branches in the year before failure and follow the same branches into the failure year

**Table 10: Acquirer Characteristics, Failure, and Deposit Rates**

This table reports heterogeneity in the effect of bank failures on \$100K deposit rates by characteristics of the acquiring bank. The specifications focus on treated events for which an acquiring bank can be inferred from SOD branch ownership, while retaining untreated observations. Column 1 tests whether the acquiring bank had at least one branch in the failed bank's county in the year before failure. Column 2 splits acquirers by size, where *Large Acquirer* indicates above-median assets among identified acquirers with observed pre-failure Call Report assets. Standard errors are clustered at the county level and reported in parentheses. \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

|                                       | (1)               | (2)              |
|---------------------------------------|-------------------|------------------|
| Bank Failed                           | 3.44***<br>(1.00) | 4.43**<br>(1.92) |
| Bank Failed x Local Acquirer Presence | 0.94<br>(1.37)    |                  |
| Bank Failed x Large Acquirer          |                   | -0.89<br>(2.91)  |
| County FE                             | Yes               | Yes              |
| Bank-Year FE                          | Yes               | Yes              |
| County Controls                       | Yes               | Yes              |
| Weights                               | County Pop.       | County Pop.      |
| Num. obs.                             | 296344            | 296337           |
| R <sup>2</sup>                        | 0.99              | 0.99             |

and the following year. When these branches subsequently appear under a different bank certificate, we classify the modal new owner as the acquirer and link the acquiring bank to Call Report data.<sup>14</sup>

Table 10 reports two tests based on the characteristics of the acquiring bank. Column 1 examines whether the acquirer already had a branch in the failed bank's county before the failure. If our results were driven by an out-of-town acquirer bringing a different pricing policy into the local market, we would expect a stronger response when the acquirer had no prior local presence. We find no such difference. Column 2 examines whether the response varies with acquirer size, where *Large Acquirer* is defined as above-median assets among acquiring banks with observed pre-failure Call Report assets. Again, we find no statistically significant difference in the deposit rate response.

<sup>14</sup>This procedure identifies an acquiring bank with a linked RSSD identifier for 93 of the 140 treated county-year events. Among the remaining events, 11 are explicitly reported by the FDIC as having no acquirer. In these cases, the SOD data generally show that the failed bank's branch network disappears rather than continuing under another bank.

These results suggest that our findings are not driven by the identity of the acquiring bank or by the deposit rates that a new acquirer brings into the local market. Consistent with this interpretation, Appendix Table A18 shows that the baseline estimate remains similar when we retain both the failed bank's local branches and the branches of acquiring banks in the sample. Taken together, the evidence points against changes in local pricing induced by the resolution process itself and toward the bank failure as the relevant event.

## IV. Model

For theoretical intuition to interpret our empirical results, we develop a static model of deposit competition with  $N$  banks, macroeconomic shocks, and bank failure. The model captures how distress in one institution reshapes the funding environment of surviving competitors through depositor behavior and incentives shaped by banks' capital positions.

### *A. Timing of the Model*

Each period  $t \in \{1, 2, \dots\}$  involves a round of static competition. There is a single macroeconomic shock variable  $\epsilon_t$  which drives loan returns from period to period following a mean-reverting process.

$$\log R_{jt}^\ell = (1 - \rho) \log \bar{R}_j^\ell + \rho \log R_{j,t-1}^\ell + \theta_j \epsilon_t \quad (5)$$

where  $\bar{R}_j^\ell$  is the steady-state return on loans,  $\rho$  governs persistence,  $\theta_j$  is bank-specific exposure, and  $\epsilon_t$  is a common shock.

At the start of period  $t$ , banks inherit their equity  $E_j$  and depositor sleepiness  $\nu_{jt}$  from the previous period. The sleepiness term captures the non-rate utility that inattentive households place on the bank and evolves as households respond to failures among competing banks. Specifically, we define

$$F_{jt} = \mathbb{I} \left\{ \max_{k \neq j} [r_{kt}^d - R_{kt}^\ell(\varepsilon_t)] > 0 \right\} \quad (6)$$

as an indicator for whether any competitor of bank  $j$  fails. Depositor sleepiness then follows a mean-reverting process:

$$\log \nu_{jt} = (1 - \rho_\nu) \log \bar{\nu}_j + \rho_\nu \log \nu_{jt-1} + \xi F_{jt-1} \quad (7)$$

where  $\bar{\nu}_j$  is the bank-specific steady-state level of depositor sleepiness and  $\xi < 0$  governs the response to failure. A failure wakes up otherwise sleepy depositors and lowers  $\nu_{jt}$ . Each bank sets its deposit rate  $r_{jt}^d$  to maximize profits as households allocate wealth across bank deposits and the money market fund. Once the deposit allocation has been made, loan returns  $R_{jt}^\ell$  are realized, and a bank fails in period  $t$  if its loan return falls short of the optimal deposit rate.<sup>15</sup> Depositors become more attentive in response to competitor failures, reducing the sleepiness term  $\nu_{jt+1}$  that passes into the next period.

## B. Depositors

A unit mass of households allocate wealth across bank deposits and a money market fund (MMF). A bank-specific fixed effect  $\delta_j$  captures persistent non-rate value arising from time-invariant amenities such as branch convenience or reputation. The time-varying component  $\nu_{jt}$  captures depositor sleepiness: the additional utility a household

<sup>15</sup>This can be viewed as a trigger for a bank run (Goldstein and Pauzner 2005, Dang, Gorton, Holmström, and Ordoñez 2017). If the bank deviates from its optimal deposit rate, then depositors recognize the bank is insolvent.

assigns to its bank while it does not actively reconsider the relationship. A competing bank's failure makes depositors reconsider their banking relationships and reduces this component of deposit utility.

Household  $i$ 's utility from depositing at bank  $j \in \{1, \dots, N\}$  at time  $t$  is

$$U_{ijt} = \alpha r_{jt}^d + \delta_j + \nu_{jt} + \varepsilon_{ijt} \quad (8)$$

where  $r_{jt}^d$  is the deposit rate,  $\alpha$  is the sensitivity to interest rates, and  $\varepsilon_{ijt}$  is an i.i.d. Type I extreme value taste shock. The sleepiness term  $\nu_{jt}$  falls when another bank fails; the rate-sensitivity parameter  $\alpha$  remains fixed. Households can alternatively invest in a money market fund offering a risk-free return  $r$ , which yields utility.

$$U_{i0t} = \alpha r + \varepsilon_{i0t} \quad (9)$$

Letting  $V_{jt} = \alpha r_{jt}^d + \delta_j + \nu_{jt}$  and  $V_{0t} = \alpha r$ , the resulting deposit market shares follow the multinomial logit form:

$$D_{jt} = \frac{\exp(V_{jt})}{\exp(V_{0t}) + \sum_{k=1}^N \exp(V_{kt})} \quad (10)$$

### C. Banks

Bank  $j$  allocates its deposit liabilities in loans. Loan returns are not perfectly known by the bank before the portfolio problem, leading to a potential default state. Banks thus have an expectation about loan returns, which pins down their portfolio problem.<sup>16</sup>

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<sup>16</sup>Because the macro-shock has mean zero and banks are risk neutral, expected profits equal the mean-reverted profits from the previous period.

Profits are given by

$$\Pi_{jt} = (R_{jt}^\ell - r_{jt}^d) \cdot D_{jt}(r_{jt}^d) \quad (11)$$

Specifically, given banks' information set at the time of deposit rate setting, bank  $j$  solves

$$\max_{r_{jt}^d} (\mathbb{E}[R_{jt}^\ell] - r_{jt}^d) \cdot D_{jt}(r_{jt}^d) \quad (12)$$

The first order condition for the optimal deposit rate for bank  $j$  is:

$$r_{jt}^d = \mathbb{E}[R_{jt}^\ell] - \frac{1}{\alpha(1 - D_{jt}(r_{jt}^d))} \quad (13)$$

#### *D. Equilibrium*

An equilibrium is characterized by deposit rates  $\{r_{jt}^d\}_{j=1}^N$ , deposit shares  $\{D_{jt}\}_{j=1}^N$ , loan returns  $\{R_{jt}^\ell\}_{j=1}^N$ , and depositor sleepiness  $\{\nu_{jt}\}_{j=1}^N$ , such that each bank optimally sets deposit rates, deposit shares follow logit demand, loan returns evolve via the macro shock process, and sleepiness adjusts to observed failures among competitors.

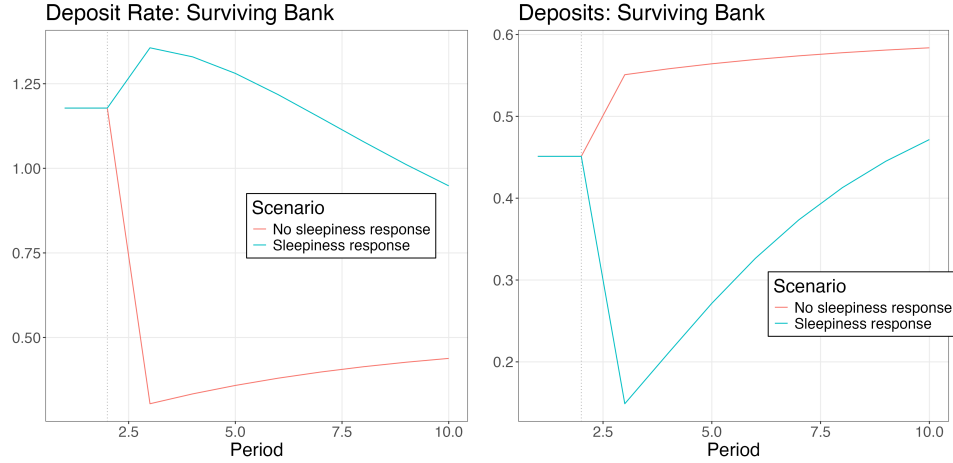
#### *E. Numerical Example*

To fix ideas, we illustrate the model in a two-bank simulation in which one institution fails following a negative macro shock. Figure 3 reports the impulse responses for the surviving bank under two scenarios. In the red line, we show the equilibrium deposit rate and deposit volumes of the surviving bank when depositor sleepiness does not respond. In the blue line, failure wakes depositors at the surviving bank.

Absent the sleepiness response, shown by the red lines, the model delivers the standard market-structure prediction. When a competitor exits, the surviving bank gains

**Figure 3: Effect of Bank Failure on Depositor Behavior**

The left panel reports the impulse response of the surviving bank's deposit rate following the failure of a competitor, while the right panel reports the corresponding deposit share response. Blue lines allow failure to wake depositors and lower sleepiness  $\nu$ , while red lines hold sleepiness fixed. The vertical dotted line marks the failure period.



pricing power. Deposit rates fall on impact while deposit quantities rise mechanically as deposits reallocate from the failed institution. As loan profitability recovers over time, deposit rates gradually increase. This case isolates the pure competition effect and corresponds to the counterfactual in which depositor demand is unchanged by failure.

When failure wakes depositors, shown by the blue lines, the model instead generates the pattern we document empirically. A competitor's failure lowers the non-rate convenience and liquidity value depositors place on the surviving bank. This shifts the deposit demand curve inward without changing  $\alpha$ , raising the surviving bank's marginal cost of funds. As a result, deposit rates increase despite the loss of a competitor, while deposit quantities fall on impact and only gradually recover as sleepiness mean reverts.

These dynamics map directly to our empirical findings along both dimensions. First, the model explains why surviving banks raise deposit rates following nearby failures even though local concentration increases. Second, the simultaneous decline in deposit quantities aligns with our evidence that higher rates do not translate into deposit in-

flows, indicating a contraction in deposit demand rather than a supply-driven repricing. Overall, the numerical example clarifies how the failure-induced dissipation of depositor sleepiness reconciles the joint behavior of deposit rates and quantities following bank failures, which cannot be explained by changes in market power or bank riskiness alone.

## V. Conclusion

Bank failures are not only destructive for the institutions that collapse, but they also reshape the competitive environment for those that remain. In this paper, we document a novel channel of propagation: a salient failure wakes otherwise sleepy depositors and shifts local deposit demand inward at surviving banks. Surviving banks raise deposit rates to stem the outflow, yet their deposit growth still falls, and survivors with high predetermined funding exposure subsequently reduce local mortgage originations relative to less-exposed banks in the same county-year. These effects are persistent, lasting multiple years, and are not confined to weak banks or uninsured deposits. Instead, they reflect a shift in depositor behavior that raises marginal funding costs and affects the broader intermediation process even when fundamentals are sound.

Our findings carry several broader implications. First, they highlight that the costs of banking crises extend beyond the balance sheet distress of failing institutions. Even solvent banks may face a more challenging funding environment, while bank mortgage issuance and the bank share of local mortgage originations decline. These spillovers can amplify the macroeconomic costs of banking crises by worsening funding conditions even for surviving banks.

Second, our results shed new light on depositor stickiness. While prior work emphasizes that deposit betas are historically low and that depositors often remain inattentive

to rate differentials, we show that these “unstuck” depositors can emerge in the wake of salient failures. This shift is not transient but leaves a persistent imprint on depositor expectations and behavior, consistent with the broader evidence that financial crises have long-lasting effects on household beliefs. Understanding how depositors toggle between inertia and vigilance is crucial for both theory and policy.

Finally, our findings underscore a key policy tradeoff in the FDIC’s resolution process. While FDIC intervention resolves failing banks and protects insured depositors, the publicity surrounding a bank failure, including the communication required to inform insured depositors, may contribute to the event’s salience and thereby affect depositors at neighboring banks. By drawing their attention, it dissipates the sleepiness that sustains deposit demand at surviving banks. The resulting demand contraction raises competitors’ funding costs, leading them to contract deposit growth and lending despite remaining solvent. Thus, the mechanism through which FDIC involvement contains failures at the institutional level can inadvertently propagate strain through the funding channel, amplifying the broader economic consequences of crises.

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## A. Appendix

### A. Additional figures and tables

**Table A1: Summary Statistics**

This table reports summary statistics for the high-cost failure sample (270 out of 543 bank failures during the sample period 2004–2021).

| A. High-cost failed banks   |                         |        |         |       |                            |       |       |       |
|-----------------------------|-------------------------|--------|---------|-------|----------------------------|-------|-------|-------|
|                             | N                       | Mean   | SD      | P25   | P50                        | P75   |       |       |
| Cost (million \$)           | 270                     | 249    | 828     | 63    | 93                         | 192   |       |       |
| Assets (million \$)         | 270                     | 1175   | 2956    | 233   | 426                        | 881   |       |       |
| Deposits (million \$)       | 270                     | 944    | 2090    | 209   | 377                        | 812   |       |       |
| B. Bank branches            |                         |        |         |       |                            |       |       |       |
|                             | N                       | Mean   | SD      | P25   | P50                        | P75   |       |       |
| CD 100K (%)                 | 62271                   | 0.378  | 0.291   | 0.150 | 0.306                      | 0.555 |       |       |
| CD 500K (%)                 | 62271                   | 0.376  | 0.289   | 0.150 | 0.304                      | 0.551 |       |       |
| Deposits (million \$)       | 62271                   | 118.37 | 1852.80 | 26.63 | 48.30                      | 86.72 |       |       |
| C. Counties                 |                         |        |         |       |                            |       |       |       |
|                             | With high-cost failures |        |         |       | Without high-cost failures |       |       |       |
|                             | N                       | Mean   | SD      | P50   | N                          | Mean  | SD    | P50   |
| N. Branches                 | 140                     | 72.42  | 120.26  | 32.50 | 2816                       | 12.80 | 21.51 | 6.60  |
| N. Banks                    | 140                     | 12.88  | 10.35   | 10.55 | 2816                       | 5.13  | 3.89  | 4.10  |
| Unemployment rate (%)       | 140                     | 6.30   | 1.55    | 6.13  | 2752                       | 6.06  | 1.98  | 5.94  |
| House price growth (%)      | 140                     | 5.13   | 3.77    | 4.71  | 2638                       | 4.62  | 2.36  | 4.40  |
| Income per capita (\$1000s) | 140                     | 44.77  | 12.73   | 42.49 | 2760                       | 40.89 | 10.67 | 38.87 |
| Population (in thousands)   | 140                     | 524    | 1070    | 202   | 2760                       | 71    | 171   | 24    |

**Table A2: Bank Failures and Deposit Rates: Bank and Year Fixed Effects**

The table reports the results from estimating Equation (1), which examines the effect of a bank failure on local competitors' deposit rates. The dependent variable is the 1-year CD rate for a \$100K deposit, measured in basis points. The sample excludes the failed bank's local branch footprint and all branches of acquiring banks. Bank Failed is an indicator for a bank failure in a county-year. Standard errors are clustered at the county level and reported in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                    | <i>r</i> <sub>100K</sub> |                |                   |                   |                    |
|--------------------|--------------------------|----------------|-------------------|-------------------|--------------------|
|                    | (1)                      | (2)            | (3)               | (4)               | (5)                |
| Bank Failed        | 2.61<br>(1.92)           | 2.45<br>(2.05) | 2.96***<br>(1.00) | 5.49***<br>(1.18) | 3.44***<br>(1.00)  |
| Unemployment Rate  |                          |                |                   |                   | 0.85***<br>(0.21)  |
| Income/Capita      |                          |                |                   |                   | −0.00***<br>(0.00) |
| Income Growth      |                          |                |                   |                   | 0.54<br>(3.04)     |
| House Price Growth |                          |                |                   |                   | −2.56<br>(2.39)    |
| Bank FE            | Yes                      | Yes            | No                | No                | No                 |
| Year FE            | Yes                      | Yes            | No                | No                | No                 |
| Bank-Year FE       | No                       | No             | Yes               | Yes               | Yes                |
| County FE          | Yes                      | Yes            | Yes               | Yes               | Yes                |
| County Controls    | No                       | No             | No                | No                | Yes                |
| Weights            | None                     | County Pop.    | None              | County Pop.       | County Pop.        |
| Num. obs.          | 321960                   | 321960         | 321960            | 321960            | 297031             |
| R <sup>2</sup>     | 0.80                     | 0.86           | 0.98              | 0.99              | 0.99               |

**Table A3: Bank Failures and Deposit Rates: Excluding Small Counties**

This table reports the results from re-estimating Equation (1) excluding small counties (i.e., population under 250,000). The dependent variable is the advertised 1-year \$100K CD rate (in basis points). Controls include local unemployment, income per capita, income growth, and house price growth. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                 | (1)               | (2)               |
|-----------------|-------------------|-------------------|
| Bank Failed     | 5.73***<br>(1.17) | 3.51***<br>(1.03) |
| County FE       | Yes               | Yes               |
| Bank-Year FE    | Yes               | Yes               |
| County Controls | No                | Yes               |
| Weights         | County Pop.       | County Pop.       |
| Num. obs.       | 112926            | 107591            |
| R <sup>2</sup>  | 0.99              | 0.99              |

**Table A4: Stacked Event Design with Matched Control Counties**

This table reports the deposit rate response in a stacked event design. Each treated county in the baseline cost-based sample forms its own stack, consisting of that county and never-treated counties matched on pre-failure local fundamentals: unemployment, income per capita, wage growth, and house price growth measured two years and one year before failure, together with log county population, compared by z-scored Euclidean distance. Each stack is restricted to the event window from two years before through three years after failure, so counties treated at other dates cannot serve as controls. Twenty-five control counties are matched to each of the 34 treated counties. Matching reduces the standardized treated-control difference in pre-failure house price growth from  $-1.26$  to  $-0.27$  and in log county population from  $1.37$  to  $0.28$ . The dependent variable is the 1-year \$100K CD rate in basis points. The specification includes county-by-event, year-by-event, and bank-year fixed effects and county controls, weights by county population, and clusters standard errors by county. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                            | $r_{100K}$        |
|----------------------------|-------------------|
|                            | (1)               |
| Bank Failed                | 2.17***<br>(0.60) |
| Matched Controls per Event | 25                |
| County-by-Event FE         | Yes               |
| Year-by-Event FE           | Yes               |
| Bank-Year FE               | Yes               |
| County Controls            | Yes               |
| Weights                    | County Pop.       |
| Num. obs.                  | 121026            |

**Table A5: Alternative Adverse Local Economic Events and Deposit Rates**

This table reports the effect of other salient local shocks on deposit rates. The dependent variable is the 1-year \$100K CD rate in basis points. Plant Closure is an indicator that turns on in and after the first plant closure involving more than 100 employees in a county. Bankruptcy is an indicator that turns on in and after the first large-firm bankruptcy is filed in a county. Bank Failed is an indicator for a bank failure in a county-year. The sample excludes the failed bank's local branch footprint and all branches of acquiring banks. Controls include local unemployment, income per capita, income growth, and house price growth. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                 | <i>r</i> <sub>100K</sub> |                 |                   |
|-----------------|--------------------------|-----------------|-------------------|
|                 | (1)                      | (2)             | (3)               |
| Plant Closure   | 0.17<br>(1.54)           |                 | 0.62<br>(1.78)    |
| Bankruptcy      |                          | -0.51<br>(1.88) | -1.09<br>(1.80)   |
| Bank Failed     |                          |                 | 3.61***<br>(1.16) |
| Bank-Year FE    | Yes                      | Yes             | Yes               |
| County FE       | Yes                      | Yes             | Yes               |
| County Controls | Yes                      | Yes             | Yes               |
| Weights         | County Pop.              | County Pop.     | County Pop.       |
| Num. obs.       | 297031                   | 297031          | 297031            |
| R <sup>2</sup>  | 0.99                     | 0.99            | 0.99              |

**Table A6: Bank Failures and Deposit Rates: State-Year Fixed Effects**

This table re-estimates Equation (1) with additional state-year fixed effects. The dependent variable is the 1-year \$100K CD rate in basis points. Bank Failed is an indicator for a bank failure in a county-year. The sample excludes the failed bank's local branch footprint and all branches of acquiring banks. Controls include local unemployment, income per capita, income growth, and house price growth. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                  | (1)               |
|------------------|-------------------|
| Bank Failed      | 1.37***<br>(0.37) |
| County FE        | Yes               |
| Bank-Year FE     | Yes               |
| State-Year FE    | Yes               |
| County Controls  | Yes               |
| Weights          | County Pop.       |
| Treated Counties | 35                |
| Num. obs.        | 287486            |
| R <sup>2</sup>   | 0.99              |

**Table A7: Bank Failures and Deposit Rates: All Failures**

This table reports the results from re-estimating Equation (1) after expanding the treatment definition to include all bank failures. The dependent variable is the 1-year CD rate of \$100K in basis points. Controls include local unemployment, income per capita, income growth, and house price growth. Standard errors are clustered at the county level and reported in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                  |                  |
|------------------|------------------|
|                  | (1)              |
| Bank Failed      | 1.42**<br>(0.71) |
| County FE        | Yes              |
| Bank-Year FE     | Yes              |
| County Controls  | Yes              |
| Weights          | County Pop.      |
| Treated Counties | 97               |
| Num. obs.        | 293442           |
| R <sup>2</sup>   | 0.99             |

**Table A8: Bank Failures and Deposit Rates by Failed Bank Footprint**

This table reports variants of Equation (1) that allow the bank failure effect to vary with the failed bank's pre-failure local deposit footprint (columns 1–2) or pre-failure local branch share (columns 3–4). The dependent variable is the 1-year CD rate of \$100K in basis points. The sample excludes the failed bank's local branch footprint and all branches of acquiring banks. Controls include local unemployment, income per capita, income growth, and house price growth. Standard errors are clustered at the county level and reported in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                  | Deposit footprint |                   | Branch share   |                  |
|------------------|-------------------|-------------------|----------------|------------------|
|                  | Small<br>(1)      | Large<br>(2)      | Small<br>(3)   | Large<br>(4)     |
| Bank Failed      | 0.58<br>(0.75)    | 4.30***<br>(1.65) | 0.71<br>(0.76) | 3.81**<br>(1.70) |
| County FE        | Yes               | Yes               | Yes            | Yes              |
| Bank-Year FE     | Yes               | Yes               | Yes            | Yes              |
| County Controls  | Yes               | Yes               | Yes            | Yes              |
| Weights          | County Pop.       | County Pop.       | County Pop.    | County Pop.      |
| Treated Counties | 62                | 29                | 57             | 36               |
| Num. obs.        | 299256            | 285401            | 299155         | 295048           |
| R <sup>2</sup>   | 0.98              | 0.99              | 0.98           | 0.99             |

**Table A9: Bank Failures and Deposit Rates: Geographic Rate Dispersion**

This table reports heterogeneity in the effect of bank failures on \$100K CD rates among rate switchers in the baseline sample. Banks are classified separately for each failure event using their observed RateWatch network in the two years before failure. Rate switchers post more than one distinct \$100K rate across at least two observed branches in either pre-failure year. High Dispersion equals one when the bank's average pre-failure within-bank-year standard deviation of \$100K rates is above the median among switchers. Bank Failed reports the response for low-dispersion switchers, and the interaction reports the differential response for high-dispersion switchers. Standard errors are clustered at the county level and reported in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                               | (1)              | (2)             |
|-------------------------------|------------------|-----------------|
| Bank Failed                   | 1.83<br>(1.78)   | 0.31<br>(1.53)  |
| Bank Failed × High Dispersion | 7.47**<br>(3.48) | 6.33*<br>(3.23) |
| County FE                     | Yes              | Yes             |
| Bank-Year FE                  | Yes              | Yes             |
| County Controls               | No               | Yes             |
| Weights                       | County Pop.      | County Pop.     |
| Num. obs.                     | 310849           | 286629          |
| R <sup>2</sup>                | 0.99             | 0.99            |

**Table A10: Bank Failures and Deposit Rates: Regional Heterogeneity**

This table reports a triple-difference version of Equation (1) that allows the bank-failure effect to vary across broad Census regions. The dependent variable is the advertised 1-year \$100K CD rate in basis points. Controls include local unemployment, income per capita, income growth, and house price growth. Standard errors are clustered at the county level and reported in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                         | (1)               | (2)               |
|-------------------------|-------------------|-------------------|
| Bank Failed x Northeast | 4.99***<br>(1.17) | 3.52***<br>(1.32) |
| Bank Failed x Midwest   | -0.10<br>(0.14)   | -0.57<br>(0.37)   |
| Bank Failed x South     | -0.00<br>(0.49)   | -0.29<br>(0.46)   |
| Bank Failed x West      | 7.90***<br>(1.58) | 4.97***<br>(1.89) |
| County FE               | Yes               | Yes               |
| Bank-Year FE            | Yes               | Yes               |
| County Controls         | No                | Yes               |
| Weights                 | County Pop.       | County Pop.       |
| Num. obs.               | 310998            | 287493            |
| R <sup>2</sup>          | 0.99              | 0.99              |

**Table A11: Bank Failures and Deposit Rates: Geographic Distance Gradient**

This table reports the effect of bank failures on deposit rates using alternative distance-based definitions of treatment. The dependent variable is the advertised 1-year \$100K CD rate in basis points. Controls include local unemployment, income per capita, income growth, and house price growth. Standard errors are clustered at the county level and reported in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                                    | (1)               |
|------------------------------------|-------------------|
| Distance from failure: 0–20 miles  | 3.76***<br>(0.73) |
| Distance from failure: 20–40 miles | 2.82***<br>(0.69) |
| Distance from failure: 40–80 miles | 0.55<br>(1.40)    |
| County FE                          | Yes               |
| Bank-Year FE                       | Yes               |
| County Controls                    | Yes               |
| Weights                            | County Pop.       |
| Num. obs.                          | 297,031           |
| R <sup>2</sup>                     | 0.99              |

**Table A12: Bank Failures and Deposit Rates across Rate Types**

This table reports estimated coefficients on Bank Failed from our baseline specification regression of each of the nine advertised non-money-market deposit rate types available in the RateWatch data. Standard errors are clustered at the county level. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                 | (1)               |
|-----------------|-------------------|
| 1-year CD, 10K  | 1.60***<br>(0.59) |
| 1-year CD, 100K | 3.44***<br>(0.98) |
| 1-year CD, 500K | 2.05***<br>(0.60) |
| Savings, 10K    | 0.23<br>(0.25)    |
| Savings, 100K   | -0.07<br>(0.28)   |
| Savings, 500K   | -0.09<br>(0.54)   |
| Checking, 10K   | 0.05<br>(0.18)    |
| Checking, 100K  | 0.17<br>(0.11)    |
| Checking, 500K  | 0.06<br>(0.14)    |
| County FE       | Yes               |
| Bank-Year FE    | Yes               |
| County Controls | Yes               |
| Weights         | County Pop.       |

**Table A13: Varying RateWatch Samples**

This table re-estimates Equation (1) for alternative RateWatch samples. Column 1 additionally admits treated branches whose first dual-product observation occurs in or after failure. Column 2 uses branch-years quoting the \$100K product but not the \$500K product. The dependent variable is the 1-year CD rate of \$100K in basis points. All specifications include county and bank-year fixed effects and county controls, weight by county population, and cluster standard errors by county. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                    | (1)               | (2)             |
|--------------------|-------------------|-----------------|
| Bank Failed        | 2.48***<br>(0.92) | -0.29<br>(0.89) |
| RateWatch Coverage | Dual, any entry   | Single product  |
| County FE          | Yes               | Yes             |
| Bank-Year FE       | Yes               | Yes             |
| County Controls    | Yes               | Yes             |
| Weights            | County Pop.       | County Pop.     |
| Num. obs.          | 302797            | 196918          |
| R <sup>2</sup>     | 0.99              | 0.99            |

**Table A14: Bank Failure Effects by Sub-period**

This table re-estimates Equation (1) separately for bank failures through 2011 (column 1) and from 2012 onward (column 2), respectively, retaining the common comparison counties and excluding treated counties from the other cohort. All specifications include county and bank-year fixed effects and county controls, weight by county population, and cluster standard errors by county. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                 | (1)               | (2)             |
|-----------------|-------------------|-----------------|
| Bank Failed     | 4.82***<br>(1.20) | -0.28<br>(0.37) |
| Failure Cohort  | Through 2011      | 2012 onward     |
| County FE       | Yes               | Yes             |
| Bank-Year FE    | Yes               | Yes             |
| County Controls | Yes               | Yes             |
| Weights         | County Pop.       | County Pop.     |
| Num. obs.       | 285198            | 285538          |
| R <sup>2</sup>  | 0.99              | 0.98            |

**Table A15: Branch Deposit Growth: Deposit Rate Analysis Sample**

This table reports the effect of a bank failure on annual log branch deposit growth, measured in percentage points, on the exact sample underlying the baseline deposit rate result in Table 1. Controls include local unemployment, income per capita, income growth, and house price growth. Standard errors are clustered at the county level and reported in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                  |                   |
|------------------|-------------------|
|                  | (1)               |
| Bank Failed      | -4.18**<br>(1.83) |
| County FE        | Yes               |
| Bank-Year FE     | Yes               |
| County Controls  | Yes               |
| Weights          | County Pop.       |
| Treated Counties | 35                |
| Num. obs.        | 252239            |
| R <sup>2</sup>   | 0.22              |

**Table A16: Bank Failures and CFPB Complaints: Common Sample**

This table re-estimates the regressions in Table 8, after restricting the sample to observations included in all four complaint categories. Standard errors are clustered at the state level and reported in parentheses. \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

|                             | Deposit accounts  | Mortgages        | Credit cards    | Credit reporting |
|-----------------------------|-------------------|------------------|-----------------|------------------|
|                             | (1)               | (2)              | (3)             | (4)              |
| First Bank Failure in State | 0.17***<br>(0.05) | 0.13**<br>(0.07) | -0.05<br>(0.05) | 0.02<br>(0.09)   |
| State FE                    | Yes               | Yes              | Yes             | Yes              |
| Bank-Year FE                | Yes               | Yes              | Yes             | Yes              |
| Num. obs.                   | 4906              | 4906             | 4906            | 4906             |
| Pseudo R <sup>2</sup>       | 0.69              | 0.90             | 0.86            | 0.98             |

**Table A17: Bank Characteristics, Failure, and Deposit Rates: Uninsured Deposits**

This table reports heterogeneity in the effect of bank failures on \$500K deposit rates by pre-existing bank characteristics. Columns 1–3 separately interact Bank Failed with Low Capital, Small Bank, and Low Net Loan Share, respectively. Each indicator equals one when the bank is in the bottom tercile of the relevant characteristic’s cross-sectional distribution in the calendar year immediately before the local failure, and the classification is held fixed throughout the event window. Standard errors are clustered at the county level and reported in parentheses. \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

|                                  | (1)                | (2)               | (3)              | (4)                |
|----------------------------------|--------------------|-------------------|------------------|--------------------|
| Bank Failed                      | 4.11***<br>(1.17)  | 2.06***<br>(0.61) | −1.58<br>(1.51)  | 0.91<br>(0.83)     |
| Bank Failed x Low Capital        | −7.39***<br>(2.82) |                   |                  | −5.07***<br>(1.33) |
| Bank Failed x Small Bank         |                    | −2.18**<br>(1.07) |                  | −0.86<br>(2.08)    |
| Bank Failed x Low Net Loan Share |                    |                   | 6.82**<br>(2.81) | 4.78***<br>(1.54)  |
| County FE                        | Yes                | Yes               | Yes              | Yes                |
| Bank-Year FE                     | Yes                | Yes               | Yes              | Yes                |
| County Controls                  | Yes                | Yes               | Yes              | Yes                |
| Weights                          | County Pop.        | County Pop.       | County Pop.      | County Pop.        |
| Num. obs.                        | 297023             | 297023            | 297023           | 297023             |
| R <sup>2</sup>                   | 0.99               | 0.99              | 0.99             | 0.99               |

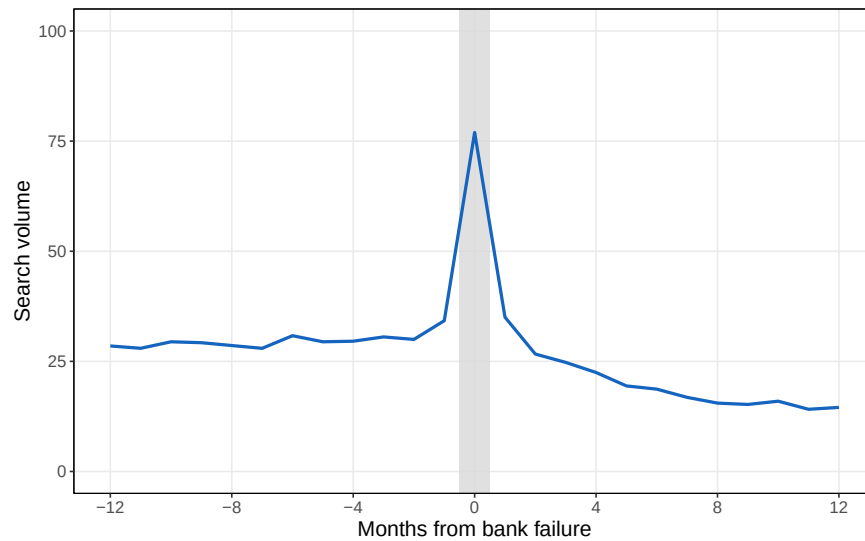
**Table A18: Bank Failures and Deposit Rates: Alternative Branch Samples**

This table reports the results from estimating Equation (1) on the unrestricted branch panel, retaining the failed bank's branches and all branches of acquiring banks that the baseline sample excludes. The dependent variable is the 1-year CD rate of \$100K in basis points. Standard errors are clustered at the county level and reported in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                 | (1)               | (2)               |
|-----------------|-------------------|-------------------|
| Bank Failed     | 4.93***<br>(1.07) | 3.14***<br>(0.88) |
| County FE       | Yes               | Yes               |
| Bank-Year FE    | Yes               | Yes               |
| County Controls | No                | Yes               |
| Weights         | County Pop.       | County Pop.       |
| Num. obs.       | 361506            | 334422            |
| R <sup>2</sup>  | 0.99              | 0.99              |

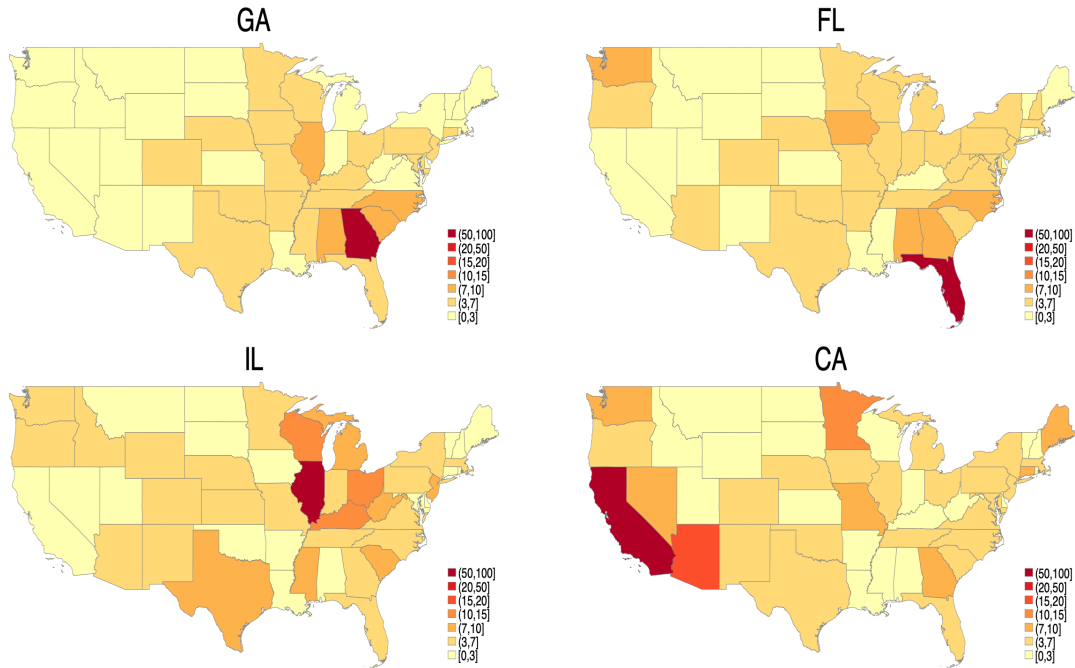
**Figure A1: Search Volume around Bank Failure**

This figure shows the normalized volume (i.e., scale of 0 to 100) of Google searches for failed banks around their failure date. The gray shaded area denotes the first month since the failure date.



**Figure A2: Search Volume by State**

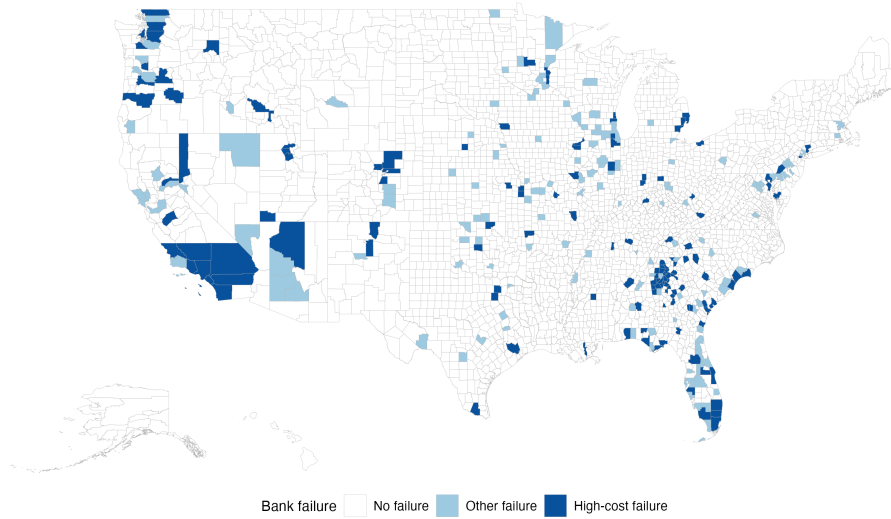
This figure shows the normalized volume (i.e., scale of 0 to 100) of Google searches for failed banks around their failure date by state for the four states with the most bank failures during our sample period: Georgia, Florida, Illinois, and California.



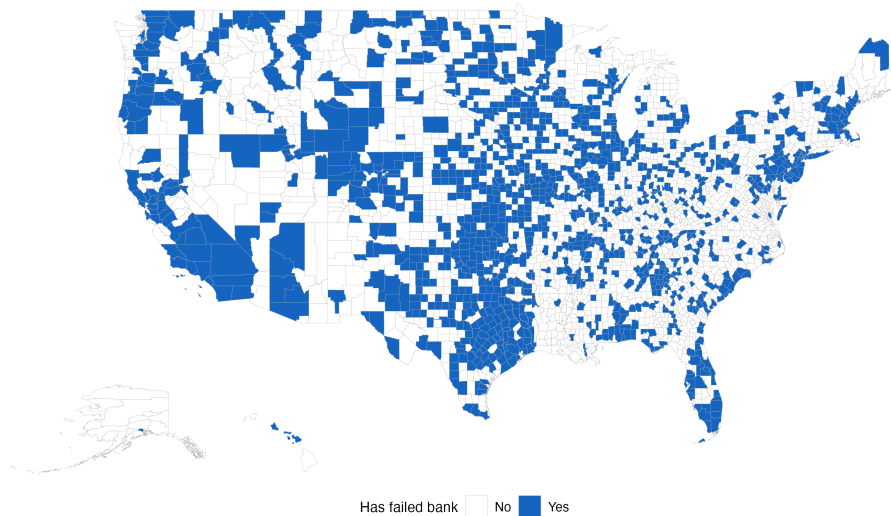
### Figure A3: Counties with Bank Failures

Panel A reports the U.S. counties with a failed commercial bank's headquarters from 2006 through 2021. Dark blue denotes the high-cost failures in the main analysis (the top half of first failures by FDIC resolution cost); light blue denotes all other failure counties. Panel B reports the counties with a failed bank's headquarters from 1934 through 2021.

**Panel A: 2006–2021**

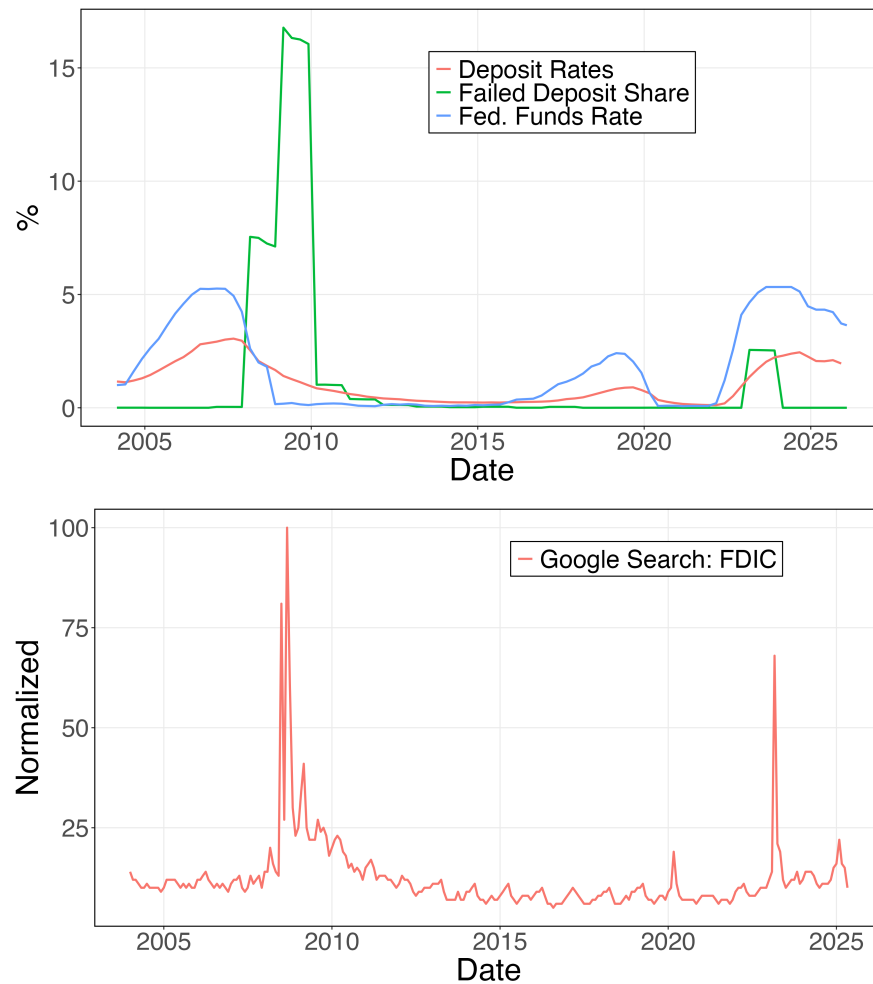


**Panel B: 1934–2021**



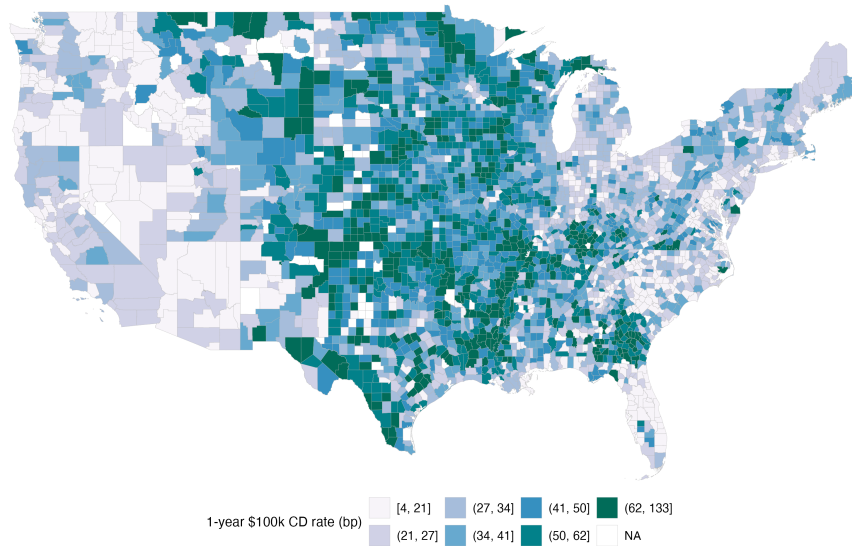
**Figure A4: Bank Failures, Interest Rates, and Attention**

The top panel reports the time series relationship between bank deposit rates and the percentage of bank deposits at institutions with recent intervention from the FDIC. The deposit rate is measured as the interest expense on domestic deposits divided by domestic deposits, obtained from the Quarterly Income and Expense of FDIC-Insured Commercial Banks and Savings Institutions. The failed deposit share is defined as the sum of deposits of banks that were either assisted or resolved by the FDIC in a given quarter, divided by the total system deposits in a quarter. The bottom panel reports the time series of aggregate search volume for FDIC on Google Trends.



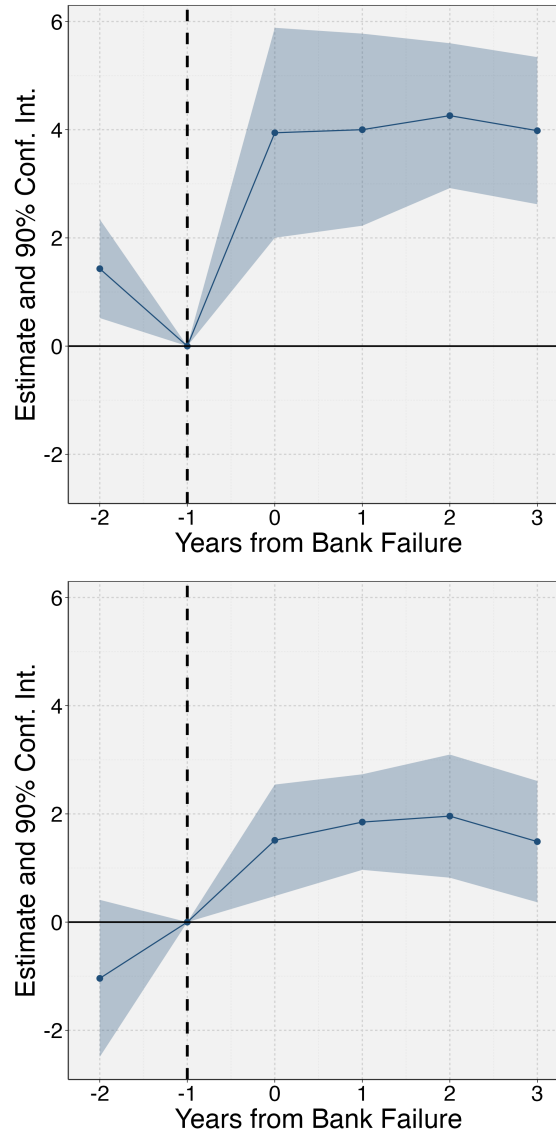
### Figure A5: Deposit Rates: Geographic Variation

This map reports the deposit-weighted 1-year \$100,000 CD rate (in basis points) across U.S. counties in 2012. Within each county, branch rates are weighted by each branch's corresponding share of total county deposits.



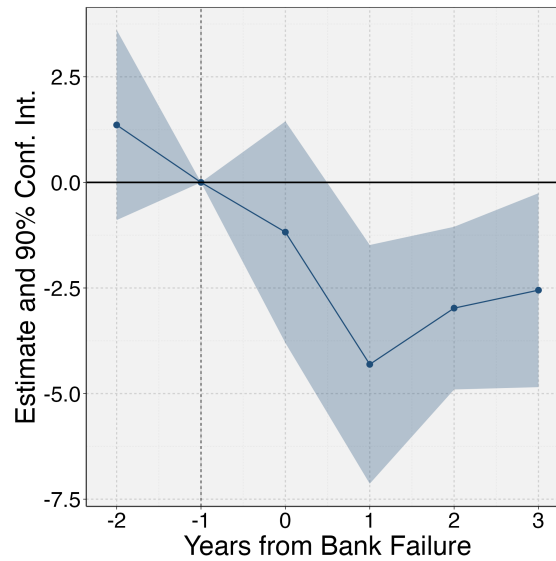
**Figure A6: Deposit Rates Dynamics with [Sun and Abraham \(2021\)](#) Estimator**

This figure shows the dynamic effect of a bank failure on local competitors' deposit rates using the specification from [Sun and Abraham \(2021\)](#). The top panel reports the \$100K result and the bottom panel reports the \$500K result. All regressions include county fixed effects and bank-year fixed effects, and additionally control for unemployment rate, income per capita, income growth, and house price growth. Standard errors are clustered at the county-level and observations are weighted by county population. The blue shaded area denotes the 90% confidence interval.



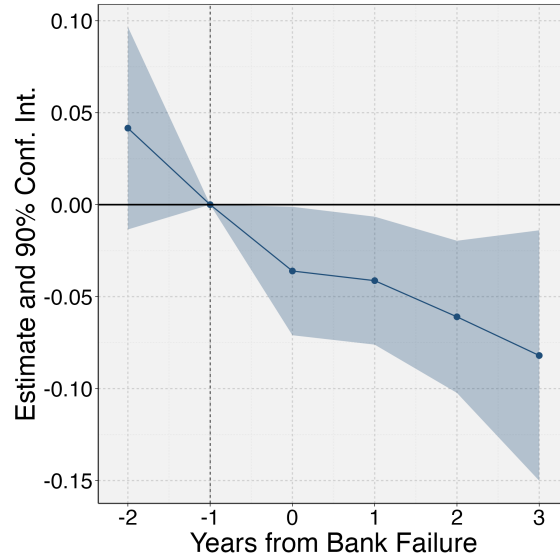
**Figure A7: Bank Failures and County Deposit Growth Dynamics**

This figure shows the dynamic effect of a local bank failure on annual county deposit growth, where county deposits are aggregated across all branches in the full FDIC Summary of Deposits. The regression includes county and year fixed effects and controls for local unemployment, income per capita, income growth, and house price growth. Standard errors are clustered at the county level and observations are weighted by county population. The blue shaded area denotes the 90% confidence interval.



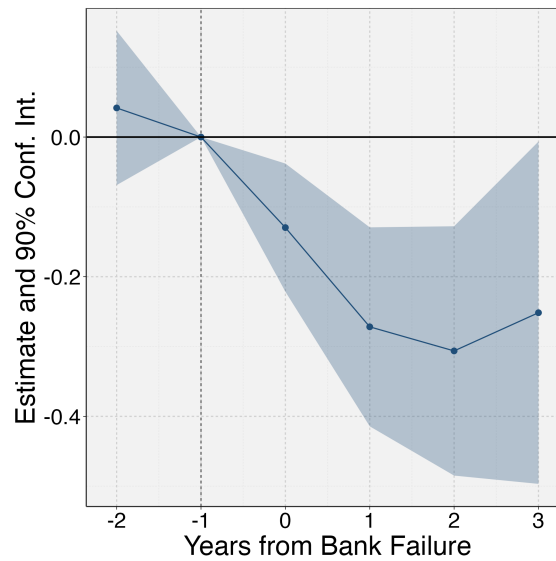
**Figure A8: Bank Mortgage Issuance Dynamics**

This figure reports annual county-year estimates for log bank HMDA mortgage origination volume. The specification includes county and year fixed effects and controls for local unemployment, income per capita, income growth, and house price growth. Standard errors are clustered at the county level. Observations are weighted by county population. The blue shaded area denotes the 90% confidence interval.



**Figure A9: High Funding Exposure and Mortgage Origination Dynamics**

This figure reports event-time coefficients from a bank-county-year PPML regression of HMDA mortgage origination volume on event-time indicators interacted with High Funding Exposure. Funding Exposure is the failure county's share of the bank's total deposits in the year before failure. High Funding Exposure identifies the top quartile of treated bank-county pairs in the mortgage estimation sample, corresponding to exposure above 15.5 percent. The omitted period is  $t = -1$ . The specification includes bank-county, bank-year, and county-year fixed effects, is weighted by county population, and two-way clusters standard errors by county and bank. Failed and acquiring banks are excluded. The blue shaded area denotes the 90% confidence interval.



### Figure A10: Bank Failures and Deposit Account-related CFPB Complaint Dynamics

This figure shows the dynamic effect of the first bank failure in a state on deposit account-related consumer complaints filed with the CFPB. The outcome is the complaint count for bank  $b$  in state  $s$  and year  $t$ ; coefficients are interpretable as log points. The regression includes bank-by-year fixed effects and state fixed effects. Standard errors are clustered at the state level. The shaded area denotes the 90% confidence interval.

