Bank Run Contagion Through Social Network*

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Abstract

This paper examines how social networks transmit bank runs, exploiting the 2023 U.S. banking crisis as a natural experiment. Leveraging Facebook's Social Connectedness Index and a difference-in-differences design, we find that banks in socially connected counties experience significantly lower deposit growth post-crisis, while geographic proximity shows no effect. Social contagion amplifies fundamental vulnerabilities, particularly for banks with high uninsured deposits and large held-to-maturity securities. However, exploiting within-bank variation reveals that fundamentals alone cannot explain the patterns: deposit outflows vary based on local social exposure even after controlling for all bank characteristics. Together, these results indicate that social contagion operates through both rational fundamental screening and panic-driven runs. We document a flight-to-safety: uninsured deposits flee while insured deposits flow in. Finally, socially-transmitted deposit shocks lead to significant credit supply contractions in both small business and mortgage lending, demonstrating substantial real economic consequences.

Keywords: Bank Runs; Social Networks; Financial Contagion; Deposit Flows

JEL Classifications: G01, G21, G28, D83, L14

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1 Introduction

The March 2023 U.S. banking crisis underscored how rapidly depositor stress can propagate in the modern financial system. Following aggressive monetary tightening that generated substantial mark-to-market losses on banks' long-duration assets, Silvergate Capital announced voluntary liquidation on March 8, and Silicon Valley Bank (SVB) collapsed within days of announcing losses and a recapitalization plan (Jiang et al., 2024). The ensuing stress quickly extended to other regional banks, including Signature Bank and later First Republic Bank, triggering system-wide deposit reallocation and prompting extraordinary regulatory intervention. The crisis exhibited substantial contagion: banks across the country experienced deposit outflows and stock price declines, many with no direct ties to the failed institutions (Choi et al., 2023; Caglio et al., 2023).

A natural question arises from the banking crisis: what mechanisms drive bank-run contagion in the digital age? Standard theories emphasize geographic proximity and direct interbank linkages (Allen and Gale, 2000; Iyer and Puri, 2012), yet the 2023 crisis suggests that modern contagion may travel through informational and coordination channels that are not geographically local. In an era where social networks capture enormous attention and facilitate rapid information diffusion, we hypothesize that *social connectedness* constitutes a distinct and economically significant channel for propagating bank distress, acting as a conduit that transmits depositor panic across socially linked regions, independent of physical distance. While recent studies examine technology-mediated transmission during the 2023 episode (Cookson et al., 2026; Choi et al., 2023), they primarily focus on financial market reactions (stock prices, trading dynamics, and online sentiment) rather than actual depositor behavior and real economic activity. A critical gap remains: do social networks transmit bank distress to deposit flows and credit supply, or do they merely amplify transitory market sentiment?

We address this gap by examining offline, real economic behavior during the 2023 crisis. Using detailed Summary of Deposits (SOD) data at the branch level and quarterly Call Reports at the bank level, we measure social ties via Facebook's Social Connectedness Index (SCI), which captures the relative intensity of friendship links between every pair of U.S. counties (Bailey et al., 2018a). We exploit the sequential bank failures as a shock to depositor beliefs and implement a difference-in-differences design that compares deposit growth at banks located in counties with high versus low social connectedness to the failed banks' headquarters, before versus after March 2023. Our key finding is that social connectedness drives actual deposit outflows, a real quantity effect, confirming that social networks serve as a transmission mechanism for bank runs, not merely a conduit for sentiment shocks. Strikingly, once we condition on social connectedness, geographic proximity has little independent explanatory power for deposit flows.

Our analysis proceeds through a deliberate narrative arc that mirrors the natural questions a skeptical reader might ask. We begin by establishing the baseline fact: banks in socially connected regions experienced significant deposit outflows following the crisis. A natural first hypothesis is that this pattern reflects rational depositor responses to bank fundamentals; perhaps social networks merely helped depositors identify banks with balance sheet vulnerabilities similar to SVB. We test this hypothesis and find strong support: social contagion is indeed amplified for banks with higher uninsured deposit ratios, larger held-to-maturity securities portfolios, and lower liquidity. These results suggest that social networks act as an attention mechanism, directing depositor scrutiny toward fundamentally weaker institutions.

However, fundamentals alone are not sufficient to explain the full extent of the observed deposit dynamics. If the crisis were driven solely by rational screening of bank balance sheets, we would expect uniform withdrawals across all branches of the same institution, since every branch of a given bank shares identical capital ratios, asset composition, and management quality. Yet we document striking heterogeneity: branches of the same bank experience dramatically different deposit flows based solely on their local social exposure to the crisis epicenter. This within-bank variation, identified through bank×time fixed effects, reveals that social networks transmit depositor stress beyond what fundamentals alone would predict. The contagion operates through two complementary channels: (1) rational information transmission that helps depositors identify vulnerable banks, and (2) panic-driven runs that spread independently of bank-level characteristics, triggered by local social exposure.

We then trace where the deposits went and document the real economic consequences. The aggregate deposit decline masks a profound compositional shift: uninsured deposits flee while insured deposits flow in, reflecting a flight-to-safety mediated by social networks. This dual pattern reveals the heterogeneous impact across depositor types: sophisticated large depositors respond to social signals by reducing exposure, while retail depositors seek the safety of insured accounts. The effect concentrates among mid-sized banks, which face significant uninsured liabilities but lack the implicit "too-big-to-fail" guarantee, while fully insured community banks and systemically important institutions remain largely insulated.

Crucially, these liability-side shocks translate into credit supply contractions with real economic consequences. Using Community Reinvestment Act and Home Mortgage Disclosure Act data, we document that banks exposed through social connections significantly contract both small business lending and mortgage originations, with the mortgage market exhibiting particularly severe retrenchment. These reductions represent economically meaningful contractions in credit availability, demonstrating that socially transmitted deposit shocks generate negative externalities that spill over into real economic activity. The social transmission channel outweighs geographic proximity in the mortgage market by a factor of 2.5, underscoring the dominance of digital contagion in modern banking crises.

Our paper contributes to the literature in four ways. First, we establish social connectedness as a distinct, economically significant channel for bank-run contagion in the digital age, moving beyond traditional geographic or interbank linkage explanations. Second, unlike studies focusing on stock prices or online sentiment, we document the impact on actual depositor behavior and the subsequent spillover to credit markets through lending contractions, capturing the *real effects* of socially mediated panic. Importantly, the observed deposit outflows cannot be attributed to banks' own strategic liability management (e.g., actively shedding costly deposits or restructuring their funding mix). In a rising-rate environment, banks might rationally allow expensive uninsured deposits to run off while replacing them with cheaper wholesale funding or retained earnings; such voluntary balance-sheet optimization would not impair lending capacity. Our evidence rules out this alternative interpretation on two grounds. First, the credit supply contractions we document, particularly the 19.7% within-bank relative decline in mortgage originations and 2.9–5.0% within-bank relative decline in small business lending at socially exposed banks, are inconsistent with voluntary deposit management: banks that strategically shed deposits would maintain or even expand lending, whereas banks facing involuntary funding shocks are forced to curtail credit to preserve liquidity buffers and regulatory capital ratios. Second, the within-bank variation in lending retrenchment across counties with different social exposure, identified through bank $\times$ year fixed effects, demonstrates that the same institution simultaneously contracts credit more aggressively in *HighSCI* counties while maintaining relatively normal lending in low-SCI counties, a pattern that cannot arise from bank-level strategic decisions but instead reflects locally varying depositor-initiated withdrawals. Third, we show how social media attention interacts with bank fundamentals: social networks act as an attention mechanism that exposes weak banks rather than indiscriminately spreading panic. Fourth, and importantly, we highlight the *persistent* nature of the effect. Unlike fleeting online rumors or momentary market volatility, the deposit outflows we observe are not transitory but exhibit persistence, suggesting a fundamental shift in banking relationships driven by social ties rather than a mere temporary panic.

Related Literature Our paper builds upon the evolving literature on financial contagion, which has historically debated the relative roles of fundamentals and panics in driving bank runs. The foundational theories emphasize maturity transformation as the root of fragility, creating multiple equilibria where self-fulfilling panics can occur (Diamond and Dybvig, 1983; Bryant, 1980). To refine these equilibria, global games frameworks suggest that the probability of a run depends critically on the precision of information available to depositors (Goldstein and Pauzner, 2005).

Historically, empirical research identified two primary structural conduits for such contagion: geographic proximity and interbank networks. Studies of the Great Depression demonstrate that contagion was largely regional, driven by local information networks and clusterings of bank failures (Calomiris and Mason, 1997; Saunders and Wilson, 1996; Calomiris and Mason, 2003). Parallel to this geographic view, a vast literature examines the interbank market as a transmission mechanism, where direct credit exposures and counterparty risk create a "domino effect" across balance sheets (Allen and Gale, 2000; Freixas et al., 2000; Mitchener and Richardson, 2019). In these pre-digital contexts, the spread of systemic risk was constrained by either physical distance or the formal architecture of financial linkages.

However, the 2023 banking crisis suggests that the influence of geography and formal interbank linkages may be evolving in an increasingly digital environment. Recent theoretical work posits that short-term debt becomes informationally sensitive during crises, triggering sudden repricing or withdrawals (Dang et al., 2020). Furthermore, a bank run can be contagious purely because of endogenous information transmission but without any direct counterparty linkage, as highlighted by the wake-up call theory (Ahnert and Bertsch, 2022). The collapse of Silicon Valley Bank (SVB) exemplifies this transition in the digital age, where realized losses on securities portfolios (Jiang et al., 2024; Flannery and Sorescu, 2023; Haddad et al., 2023) triggered a systemic wake-up call. Crucially, the transmission of this shock was less constrained by traditional geographic lines or formal interbank exposures than in previous episodes, highlighting the role of social connection channels. While Cookson et al. (2026) identify a "social media multiplier" effect via Twitter, we argue that underlying social networks—long-term, trusted interpersonal ties—serve as the structural infrastructure for this information transmission, operating distinctly from both high-frequency social media noise and geographical proximity.

A growing body of work has clarified the sources of fragility and documented the resulting deposit dynamics during the 2023 crisis. On the structural side, Jiang et al. (2024) estimate that interest rate increases from 2022Q1 to 2023Q1 implied large aggregate valuation losses and develop a model in which uninsured funding can trigger self-fulfilling *solvency* runs even when bank assets are liquid. Relatedly, Drechsler et al. (2026) emphasize "deposit franchise runs," where fragility arises because a bank's future deposit profits vanish when uninsured depositors withdraw. On the empirical side, Cipriani et al. (2024) use high-frequency payments data to identify run-like outflows at 22 banks in a narrow window around SVB's failure, with deposit flight disproportionately directed toward the largest banks. Consistent with this system-wide reallocation, Caglio et al. (2024) document a flight-to-safety toward large banks using confidential weekly data and show that banks suffering the largest outflows subsequently contract lending. While these frameworks clarify *why* runs can occur and *where* deposits flow in the modern banking system, they do not pin down *how* panic spreads in the cross-section; that is, they leave open the question of which transmission mechanism links a localized bank failure to depositor withdrawals at distant, seemingly unrelated institutions.

To measure social ties, we utilize the Social Connectedness Index (SCI) introduced by Bailey et al. (2018a). This literature establishes social networks as a critical non-price mechanism for economic coordination, facilitating trade, patent citations, and migration flows (Bailey et al., 2018a, 2021, 2024). In finance, existing research on social networks has predominantly focused on the asset side of balance sheets or the upside of investment behavior. For instance, social connections have been shown to drive housing market beliefs (Bailey et al., 2018b, 2019), stock market participation and reaction (Kuchler et al., 2022a; Hirshleifer et al., 2025; DeLisle et al., 2022), and institutional investor contagion (Au et al., 2024). On the lending side, Rehbein and Rother (2025) finds that banks lend significantly more to socially connected borrowers, and Griffin et al. (2025) highlight a darker side of connectivity: social networks facilitate the contagion of fraud.

A significant gap remains regarding the liability side of financial intermediaries, particularly how social networks undermine funding stability during stress. While Flynn and Wang (2025) and Cramer and Koont (2021) provide initial evidence that social ties influence deposit levels, our paper distinguishes itself by exploiting the 2023 crisis to isolate the transmission of panic and the specific direction of flows. We contribute by demonstrating that social contagion operates through two distinct channels: rational fundamental screening and panic beyond fundamentals. Unlike the broad peer effects in consumption or insurance (Bailey et al., 2022; Hu, 2022), we document a directional mechanism where social networks channel funds away from vulnerable banks, with heterogeneous effects across depositor types and bank characteristics.

Finally, our work contributes to the literature on depositor behavior by linking social transmission to depositor heterogeneity. Traditional models often treat depositors as a homogenous block or focus on aggregate market power (Drechsler et al., 2017; Li et al., 2023; Becker, 2007). However, the 2023 crisis underscored the critical role of uninsured depositors, who are highly sensitive to solvency signals (Iyer and Puri, 2012; Iyer et al., 2016; Artavanis et al., 2022). We connect this sensitivity to the social transmission bias framework of Hirshleifer (2020), which suggests that social processes amplify behavioral responses to economic shocks. In the context of banking, this amplification manifests as a flight-to-safety. Caglio et al. (2023) document a broad migration of funds from regional to large banks, and Traweek and Wardlaw (2025) show that sophisticated depositors exit early to avoid losses. We bridge these findings by demonstrating that social networks are the conduit for this flight. Specifically, we show that social ties do not merely trigger indiscriminate withdrawals (as in a pure panic) but facilitate a sophisticated reallocation: uninsured deposits leave, while insured deposits arrive. This nuance redefines social networks not just as a source of contagion, but as a mechanism for the rapid, albeit destabilizing, repricing of bank risk by information-sensitive agents.

Roadmap The remainder of the paper proceeds as follows. Section 2 presents the institutional background and develops our research hypotheses. Section 3 describes the data and variable construction. Section 4 presents the empirical strategy. Section 5 establishes the baseline bank-level evidence of social contagion. Section 6 examines how bank fundamentals amplify the effect. Section 7 provides branch-level evidence that social panic operates beyond fundamentals. Section 8 traces deposit reallocation dynamics. Section 9 examines real economic consequences through credit supply contractions. Section 10 concludes.

2 Background and Hypotheses

2.1 The 2023 Banking Crisis

In March 2023, the U.S. banking sector experienced a sudden crisis. The crisis originated from the Federal Reserve's aggressive monetary tightening: between March 2022 and March 2023, the federal funds rate rose from near zero to over 4.5 percent, generating substantial unrealized losses on banks' long-duration securities portfolios. These losses severely eroded capital at institutions with high concentrations of held-to-maturity (HTM) assets and uninsured deposits. On March 8, 2023, Silvergate Bank announced voluntary liquidation following massive deposit outflows. Two days later, SVB, whose unrealized losses roughly equaled total equity and whose deposit base was 88 percent uninsured, suffered a $42 billion single-day withdrawal and was closed by banking regulators. The panic immediately spread: Signature Bank lost approximately 20 percent of its deposits within hours and was placed into FDIC receivership on March 12; First Republic Bank lost approximately $100 billion in deposits during March alone, including a $25 billion single-day outflow on March 10, prompting an emergency $30 billion deposit injection from eleven major banks on March 16 and a downgrade to junk status by S&P on March 19, before ultimately being seized in May (Federal Deposit Insurance Corporation, 2023). In response, the U.S. Treasury, Federal Reserve, and FDIC jointly invoked the systemic risk exception on March 12 to guarantee all deposits, including those exceeding the $250,000 statutory limit, at SVB and Signature, and established the Bank Term Funding Program (BTFP) to provide liquidity against collateral valued at par.[1] Figure A.1 in the onlien appendix provides a visual timeline of these key events.

[1] By end-2022, unrealized losses on available-for-sale and HTM securities exceeded $600 billion across the banking system, with mark-to-market declines estimated above $2 trillion (Board of Governors of the Federal Reserve System, 2023b). Detailed crisis chronology and regulatory responses are documented in Federal Deposit Insurance Corporation (2023), Bank for International Settlements (2023), U.S. Department of the Treasury et al. (2023), and Board of Governors of the Federal Reserve System (2023a).

This episode provides an ideal setting to study contagion mechanisms: the failures were sudden and largely unanticipated, driven by balance-sheet vulnerabilities orthogonal to traditional credit quality concerns, and the geographic concentration of failed institutions in California and New York creates substantial cross-sectional variation in both social and geographic exposure to the shock.

2.2 Hypothesis Development

The 2023 episode departs from traditional contagion patterns. The failed banks had limited interbank exposures, and panic spread to institutions thousands of miles from California and New York, suggesting that neither direct credit linkages nor geographic proximity can fully explain the observed contagion. What distinguishes this crisis is the informational environment. Social networks, that is, long-term interpersonal ties, provide a parallel infrastructure for transmitting crisis-relevant information regardless of physical distance. Intuitively, social networks serve the information transmission channels stressed by the wake-up call theory of financial contagion (Ahnert and Bertsch, 2022). While existing studies document a "social media multiplier" through platforms such as Twitter (Cookson et al., 2026), high-frequency social media noise is distinct from the deeper influence of underlying social connectedness. We argue that the structural fabric of social ties, not merely viral content, serves as the primary conduit for cross-regional contagion.

H1: **Social connectedness to crisis epicenters amplifies deposit outflows.**

If social networks transmit depositor stress, through what mechanism? One possibility is an *information attention* channel: social connections expose depositors to news about the SVB collapse, heightening scrutiny of local banks and directing attention toward institutions with similar vulnerabilities (high uninsured deposit ratios, large HTM portfolios, and low liquidity buffers). Under this view, social contagion is fundamentally rational: it accelerates the process by which depositors identify pre-existing weaknesses that had not yet triggered withdrawals. However, if this were the only channel, all branches of a given bank, sharing identical fundamentals, should experience similar deposit flows. If branches of the *same* bank in more socially connected counties suffer larger outflows, social networks must also transmit a panic component that operates *beyond* bank-level characteristics.

H2: **Social contagion operates through two complementary channels: (a) an**

information attention channel, where social networks direct depositor scrutiny toward banks with greater fundamental vulnerabilities, and (b) a panic channel, where social exposure triggers deposit outflows independently of bank-level characteristics.

The preceding hypotheses concern the liability side of bank balance sheets. Yet the economic significance of socially transmitted runs depends on whether funding shocks spill over into the real economy. If deposit outflows are sufficiently large, affected banks may curtail lending, generating credit supply contractions that harm borrowers with no direct connection to the original crisis. Documenting real effects also serves an identification purpose: a bank that voluntarily sheds costly deposits would not simultaneously contract credit supply, whereas a bank facing involuntary funding shocks is forced to reduce lending. Observing that socially exposed banks cut small business lending and mortgage originations therefore confirms that deposit declines reflect depositor-initiated withdrawals.

H3: **Socially transmitted deposit shocks generate credit supply contractions in the real economy.**

2.3 Overview of the Identification Strategy

Our identification strategy leverages the March 2023 failures as an exogenous shock to depositor beliefs. We measure social ties using Facebook's Social Connectedness Index (SCI), which quantifies friendship link intensity between every pair of U.S. counties (Bailey et al., 2018a).

The core of our identification is a comparison of deposit flows across areas with varying social connectedness to the crisis epicenters, before and after March 2023, while simultaneously controlling for physical distance to failed bank locations. We analyze deposit flows at both the bank level (quarterly regulatory filings) and the branch level (annual data for every individual branch). The branch-level analysis compares branches of the *same bank* in different counties, controlling for all bank-specific factors, including capital adequacy, liquidity, business model, and reputation, that might independently affect deposit stability.

3 Data

The analysis in this study relies on three primary datasets: the Social Connectedness Index (SCI) from Facebook, quarterly Call Reports for U.S. banks, and the annual Summary of Deposits (SOD) branch-level data provided by the Federal Deposit Insurance Corporation (FDIC).

To measure the intensity of social relationships, we use the Social Connectedness Index (SCI) provided by Facebook, which is based on the metric developed by Bailey et al. (2018a). The SCI quantifies social ties between counties by calculating the number of Facebook connections linking users in county i and county j. This connection count is normalized by the product of total Facebook users in each respective county:

$$\text{Social Connectedness}_{i,j} = \frac{\text{connection}_{i,j}}{\text{user}_i \times \text{user}_j} \tag{1}$$

The SCI data that we utilize represents the original Social Connectedness value for each county pair, scaled by dividing it by the maximum value in the dataset and then multiplying the result by 1 billion. This procedure ensures all SCI values fall within a range of 1 to 1 billion. The index captures the comparative likelihood of Facebook friendship links between any two counties, thereby providing pairwise social connectedness metrics across all county combinations. Figure 1 illustrates the geographic distribution of average social connectedness to the headquarters counties of the four failed banks. Figure A.2 further presents the social connectedness distribution for each of the four failed banks individually.

[Insert Figure 1 here]

It is important to clarify that the SCI does not measure explicit Facebook interactions, such as content sharing or messaging. Consistent with prior research employing SCI data (e.g., Flynn and Wang, 2025), we use the index as a proxy for real-world social relationships, rather than online social media engagement. The SCI is computed from an anonymized snapshot of active Facebook users' friendship links (Meta Data for Good, 2020). Facebook primarily serves to connect individuals with existing real-life contacts, meaning the index reflects enduring social bonds that remain generally stable over time. Nevertheless, we conduct robustness tests to verify that our findings are not affected by unobserved temporal variations in social connections resulting from population migration.

We obtain quarterly financial indicators for U.S. banks from Call Reports, covering the period from the first quarter of 2020 through the second quarter of 2024. These regulatory filings contain comprehensive information on banks' financial condition, including balance sheet items, income statements, and capital adequacy metrics. The specific variables extracted from these datasets and their definitions are detailed in the Appendix. Additionally, we use the SOD data from 2021 to 2024, which provides annual data on branch locations and deposit information.

To investigate the underlying mechanisms of contagion and their real economic consequences, we supplement our core financial data with two additional datasets. First, to examine the spillover effects on credit supply, we use data from the Community Reinvestment Act (CRA) regarding small business lending. Second, we use data from the Home Mortgage Disclosure Act (HMDA) to analyze mortgage market dynamics. For both lending datasets, we aggregate the data to the bank-county-year level to measure changes in total loan amounts and the number of loan originations.

Our analysis incorporates supplementary control variables, including county-to-county geographic distances (NBER County Distance Database),[2] COVID-19 case and death rates (New York Times), federal funds rate data (Federal Reserve), and local socioeconomic indicators such as GDP growth and population changes (American Community Survey). We present basic statistics for all primary variables in Table 1.

[Insert Table 1 here]

4 Empirical Strategy

Building on the 2023 banking crisis described above, we exploit these bank failures as an exogenous shock to identify the causal effect of social connections on deposit flows. This setting is particularly well-suited for our identification strategy for three reasons. First, the rapid and unexpected nature of the failures, particularly SVB's closure within days,

[2] For more details, see https://www.nber.org/research/data/county-distance-database.

minimizes anticipatory responses. Second, the failures were driven by balance-sheet vulnerabilities orthogonal to traditional credit quality concerns that might correlate with our social connection measures (Manski, 1993; Bursztyn et al., 2014). Third, the geographic concentration in California and New York creates substantial cross-sectional variation in both social and geographic exposure to the shock.

We implement a difference-in-differences (DID) approach to examine how social connection intensity influences deposit flows in the aftermath of the crisis. Following Au et al. (2024), we categorize banks and their branches based on social distance to failed bank locations, dividing our sample along the median value of social connectedness into a high social connection group (*HighSCI*) and a low social connection group (*LowSCI*), which serve as our treatment and control groups, respectively.

4.1 Bank-Level Specification

To analyze the impact of social connections, we construct a regression model at the bank-level that allows us to identify the differential effects of social connectedness and geographic proximity on deposit flows following the banking crisis. Our specification is as follows:

$$\begin{aligned} DepGr_{b,r,t} = {} & \alpha_1 HighSCI_r \times Post_t + \alpha_2 LowGeo_r \times Post_t \\ & + \beta_0 Covid_{r,t} + \beta_1 Covid_{r,t} \times HighSCI_r + \beta_2 Covid_{r,t} \times LowGeo_r \\ & + \gamma_1 \Delta MP_t \times HighSCI_r + \gamma_2 \Delta MP_t \times LowGeo_r \\ & + \mathbf{X}_{b,r,t} + \mu_r + \lambda_t + \phi_b + \epsilon_{brt}, \end{aligned} \tag{2}$$

where the subscripts denote bank (b), county (r), and time or year-quarter (t). In this model, the dependent variable $DepGr_{i,r,t}$ measures bank deposit flows as the year-over-year logarithmic growth rate of deposits in each quarter, with positive values indicating net deposit inflows and negative values indicating outflows. The dummy variable $Post_t$ equals one for periods after March 2023 when the bank runs had already occurred. Our primary variables of interest are $HighSCI_r$, which equals one for counties with above-median social connection strength to counties where failed banks had their headquarters, and $LowGeo_r$, which equals one for counties with below-median geographic distance to failed bank headquarters locations.[3] Additionally, we account for potential confounding factors by controlling for COVID-19 pandemic effects, measured as the ratio of new cases to population in each county, and monetary policy changes, captured by the quarterly Federal Funds rate adjustments (ΔMP_t), both interacted with our main treatment variables. The model includes a comprehensive set of controls ($\mathbf{X}_{b,r,t}$) at both bank and county levels. We include county (μ_r), time (λ_t), and bank (ϕ_b) fixed effects to absorb unobserved heterogeneity across these dimensions.[4]

4.2 Branch-Level Specification

Extending our analysis to the branch level, we adopt a similar identification strategy to examine how social connections influence deposit flows at a more granular level. This approach allows us to capture potential heterogeneity in depositor behavior across different branches of the same bank. Our branch-level specification is as follows:

$$\begin{aligned} DepGr_{i,r,t} = {} & \alpha_1 HighSCI_r \times Post_t + \alpha_2 LowGeo_r \times Post_t \\ & + \beta_1 Covid_{r,t} \times HighSCI_r + \beta_2 Covid_{r,t} \times LowGeo_r \\ & + \gamma_1 \Delta MP_t \times HighSCI_r + \gamma_2 \Delta MP_t \times LowGeo_r \\ & + \mathbf{X}_{r,t} + \phi_i + \gamma_{b,t} + \epsilon_{i,r,t}, \end{aligned} \tag{3}$$

[3] A concern in multi-treatment linear regressions is "contamination bias": coefficients generally do not recover convex averages of heterogeneous treatment effects and can be contaminated by non-convex combinations of other groups' effects (Goldsmith-Pinkham et al., 2024). To mitigate this issue and because we have only a few treated headquarters counties, we exclude counties where failed banks were headquartered (and, in branch-level tests, counties containing failed-bank branches). This also avoids mixing our analysis with post-failure structural breaks (e.g., FDIC receivership) and improves inference with few treated clusters (Alvarez et al., 2025).

[4] We control for COVID-19 severity and monetary tightening and allow their effects to differ across exposure groups. COVID-19 spread along pre-existing social ties beyond geographic proximity (Kuchler et al., 2022b), and local pandemic intensity affected deposit pricing and inflows (Levine et al., 2020) as well as core deposits and lending (Dursun-de Neef and Schandlbauer, 2022). Monetary tightening triggers deposit outflows with heterogeneous incidence across markets (Drechsler et al., 2017); deposit pass-through rises in high-rate environments (Greenwald et al., 2023; Emin et al., 2025), and online banks adjust more and attract inflows (Erel et al., 2023). The May 2023 Financial Stability Report notes deposit outflows during 2022, especially among banks with more runnable uninsured deposits (Board of Governors of the Federal Reserve System, 2023c). Accordingly, we interact these confounds with $HighSCI_r$ and $LowGeo_r$ so differential exposure does not load onto our estimated social-contagion effects.

where the subscripts denote individual branch (i), county (r), time or year (t), and bank (b). The dependent variable $DepGr_{i,r,t}$ measures branch-level deposit annual growth rates, winsorized at the 1% and 99% levels to mitigate the influence of outliers. The variable $Post_t$ indicates the occurrence of bank run events. Our main variables of interest remain $HighSCI_r$, indicating whether a branch's county has above-median social connection strength with counties where failed banks had branches (averaged across all branches if failed banks had multiple locations), and $LowGeo_r$, indicating whether a branch's county has below-median geographic distance to failed banks' counties. We account for pandemic effects through $Covid_{r,t}$, measured as the ratio of annual infections to population. Monetary policy changes are captured by ΔMP_t, measured as the annual change in the Federal Funds rate. The model includes county-level socioeconomic variables in $\mathbf{X}_{r,t}$, while incorporating branch fixed effects (ϕ_i) and bank-by-time fixed effects ($\gamma_{b,t}$).

This branch-level model offers several advantages for identifying the role of social connections in bank run contagion. By controlling for branch fixed effects (ϕ_i), we eliminate the influence of time-invariant branch characteristics. Simultaneously, the inclusion of bank-by-time fixed effects ($\gamma_{b,t}$) absorbs any shocks common to all branches of the same bank in a given period, allowing us to isolate the differential impact of social connections across branches of the same institution.

5 Bank-Level Results

This section establishes the causal link between social connectedness and deposit stability during the 2023 banking crisis. We document that banks embedded in communities with strong social ties to failed institutions experienced significant deposit outflows, while geographic proximity played no discernible role. These findings provide the first evidence that the crisis propagated as a "digital run" through information networks rather than a conventional regional crisis.

5.1 Baseline Results

Table 2 reports difference-in-differences estimates comparing deposit growth at banks in counties with high versus low social connectedness to the headquarters of the four failed banks (Silicon Valley Bank, Signature Bank, Silvergate Bank, and First Republic Bank).

[Insert Table 2 here]

Banks embedded in communities with strong social ties to the failed institutions suffered a sharp contraction in deposit funding. As shown in Column (5), these banks experienced a 1.98 percentage point decline in deposit growth relative to unconnected peers following the crisis—an economically meaningful 0.16 standard deviation drop. This retrenchment is consistent with the hypothesis that social networks served as conduits for panic, rapidly transmitting information about bank fragility to depositors who then withdrew funds as a precautionary measure.

Crucially, this contagion effect is distinct from traditional geographic spillovers. While one might expect local economic linkages to drive deposit withdrawals, we find that physical proximity played no discernible role. After accounting for social linkages, being geographically close to a failed bank predicted no differential change in deposit flows (Column 5). This result strongly suggests that the 2023 banking panic was a "digital run" propagated through information networks rather than a conventional regional crisis driven by local economic fundamentals.

5.2 Dynamic Effects and Parallel Trends

To verify that our results capture a causal response to the crisis rather than pre-existing secular trends, we map the dynamic evolution of deposit growth in Figure 2. The event study confirms the validity of our empirical design. Prior to the March 2023 shock, banks in *HighSCI* counties tracked their low-SCI peers closely, with coefficient estimates statistically indistinguishable from zero. This lack of pre-trends supports the parallel trends assumption underlying our difference-in-differences strategy.

[Insert Figure 2 here]

Immediately following the collapse of SVB, connected banks witnessed a sudden and persistent divergence. In the first quarter post-crisis (Q1 2023), deposit growth fell sharply, a decline that intensified over the subsequent year relative to the control group. By the third quarter post-crisis ($t+5$), the cumulative relative decline reached approximately 2.67

percentage points. This persistence suggests that the social signal generated a lasting shift in depositor sentiment rather than a momentary panic. In contrast, and consistent with the regression results, geographic proximity yields no consistent dynamic pattern, further identifying social connectedness as the primary transmission mechanism.

We rigorously stress-test this result using placebo exercises summarized in Figure A.3. Neither artificially shifting the event date (Time Placebo) nor randomly shuffling treatment assignments across counties (Spatial Placebo) generates estimates comparable to our baseline findings. The probability of observing our main result by chance is effectively zero, reinforcing that social proximity to the failing banks captured a fundamental economic transmission channel.

5.3 Robustness Checks

We subject our main findings to a battery of robustness checks in Tables A.3 and A.4 to ensure the results are not artifacts of measurement choices.

First, the results hold regardless of how we define the shock. Whether we define the "failed banks" as the full set of three (SVB, SIB, SGB), just the California banks, or include First Republic, the negative impact of social connectedness remains stable and statistically significant. Second, the functional form of the variable does not drive the result: using continuous measures of social connectedness or alternative thresholds (75th percentile) yields identical conclusions.

Finally, we confirm that the results persist across alternative definitions of the dependent variable. Whether measuring deposit flows as level changes, asset-scaled flows, or a binary indicator for negative growth, socially connected banks consistently underperform. This resilience across specifications provides high confidence that the estimated coefficients capture a structural economic relationship: social networks act as a critical infrastructure for the propagation of financial distress.

6 Bank Fundamentals

Having established that social networks transmitted deposit shocks during the 2023 crisis, we now investigate whether this contagion was indiscriminate or whether it selectively targeted banks with specific vulnerabilities. A natural hypothesis is that depositors used social information to identify institutions resembling the failed banks in terms of balance sheet composition and funding structure. If social networks merely amplified rational screening based on fundamentals, we should observe that the contagion effect concentrates among banks with characteristics similar to SVB and Signature Bank.

We test this hypothesis by examining three dimensions of bank fragility that theory and the crisis timeline identify as critical: uninsured deposit concentration, held-to-maturity securities exposure, and asset illiquidity. Table 3 reports the results, interacting our social connectedness measure with each vulnerability indicator.

[Insert Table 3 here]

6.1 Uninsured Deposit Concentration

The reliance on uninsured deposits, defined as deposits exceeding the $250,000 FDIC insurance limit, proved to be the most critical structural vulnerability. Column 1 of Table 3 reveals that the social contagion effect was dramatically amplified for banks with high uninsured deposit ratios. This finding directly echoes the SVB experience, where uninsured deposits constituted over 90 percent of total deposits, enabling a $42 billion single-day withdrawal when sophisticated depositors recognized their exposure to potential losses (Federal Deposit Insurance Corporation, 2023).

Theoretically, uninsured depositors serve as private monitors of bank solvency (Iyer and Puri, 2012; Artavanis et al., 2022). Unlike insured retail depositors who face no incentive to scrutinize bank fundamentals, large depositors holding balances above the insurance threshold bear direct downside risk and thus respond aggressively to adverse signals. Recent theoretical work on "deposit franchise runs" (Drechsler et al., 2026) emphasizes that uninsured funding creates a discontinuous fragility: once triggered, these depositors flee en masse, collapsing the bank's funding base. Our results confirm this mechanism operated through social networks during the 2023 crisis. Social ties to failed bank regions acted as an attention mechanism, prompting large depositors to reassess their exposure. Banks resembling the failed institutions, i.e., those with high uninsured deposit shares, faced the sharpest withdrawals, consistent with depositors using the social signal to identify institutions vulnerable to the same uninsured-deposit run dynamics.

Interestingly, geographic proximity to failed banks appears to have played a *protective* role for banks with high uninsured deposits (Column 1). This counterintuitive result may reflect the buffer provided by local relationship banking: depositors with long-standing ties to nearby institutions may have been less inclined to run despite structural similarities to failed banks, suggesting that physical proximity strengthens trust and loyalty in ways that offset pure balance-sheet concerns.

6.2 Held-to-Maturity Securities Exposure

The second dimension of amplification centers on banks' portfolios of held-to-maturity (HTM) securities. Column 2 demonstrates that banks carrying large HTM positions experienced significantly more severe deposit outflows in socially connected counties. This channel directly maps to the root cause of the SVB collapse: the Federal Reserve's rapid monetary tightening between March 2022 and March 2023 caused the market value of long-duration fixed-income securities to plummet, generating massive unrealized losses that eroded economic capital (Jiang et al., 2024).

Under current accounting standards, HTM securities are reported at amortized cost rather than fair value, allowing banks to avoid recognizing mark-to-market losses on their balance sheets. However, this accounting treatment creates a latent fragility: if depositors withdraw funds and force liquidation, unrealized losses crystallize into actual capital destruction. By end-2022, unrealized losses on HTM and available-for-sale securities exceeded $600 billion across the U.S. banking system (Board of Governors of the Federal Reserve System, 2023b). For institutions like SVB, where unrealized losses roughly equaled total equity, this vulnerability was existential.

Our findings suggest that depositors in socially connected regions used information about SVB's HTM-driven failure to screen other banks for similar exposure. Social networks effectively transmitted not just panic, but *diagnostic criteria* for identifying vulnerable institutions. Banks with large HTM portfolios were scrutinized and penalized by depositors who recognized the parallel to SVB's balance-sheet structure. This pattern is consistent with theories of information-sensitive debt (Dang et al., 2020): during crises, short-term creditors (including depositors) suddenly become attentive to risks previously ignored, triggering repricing or withdrawal. Social connections served as the conduit through which this diagnostic information diffused, enabling depositors to discriminate between safe and fragile banks based on balance-sheet composition.

6.3 Asset Illiquidity

The third fragility dimension, asset illiquidity, yields a weaker but still discernible amplification effect (Column 3). Following Berger and Bouwman (2009), we construct a comprehensive measure of bank liquidity creation that captures the extent to which banks transform illiquid assets into liquid liabilities. We extend their methodology to our sample period and use the inverse of this measure (scaled by total assets) to proxy for asset illiquidity. Traditional banking theory, exemplified by the Diamond-Dybvig model (Diamond and Dybvig, 1983), emphasizes that maturity transformation inherently exposes banks to liquidity risk: if too many depositors demand early withdrawal, banks must liquidate long-term assets at fire-sale prices, potentially triggering insolvency. This liquidity channel has historically been central to explanations of bank runs.

However, the 2023 crisis suggests that pure liquidity constraints played a less decisive role than balance-sheet solvency concerns. Unlike classic liquidity-driven runs where banks face mechanical cash shortfalls, SVB's failure stemmed primarily from capital erosion due to unrealized securities losses rather than an inability to meet withdrawal requests per se. The Federal Reserve's rapid deployment of the Bank Term Funding Program (BTFP), which allowed banks to borrow against securities valued at par rather than market prices, effectively neutralized the immediate liquidity pressure (Board of Governors of the Federal Reserve System, 2023a).

Our empirical results align with this narrative. While asset illiquidity does amplify social contagion, the magnitude is smaller than the effects observed for uninsured deposit concentration and HTM exposure. This suggests that depositors were primarily concerned with *solvency* (whether banks had sufficient capital to absorb losses) rather than *liquidity* (whether banks could physically produce cash). In other words, the 2023 banking panic was fundamentally a "solvency run" driven by concerns about unrealized losses and the fragility of uninsured funding, rather than a classic "liquidity run" driven by mechanical cash constraints (Jiang et al., 2024).

Taken together, these results demonstrate that social networks act as an attention mechanism that directs depositor scrutiny toward banks with structural vulnerabilities resembling those of failed institutions. The contagion is not indiscriminate but rather *selective*, targeting banks with high uninsured deposit ratios and large HTM portfolios, the precise combination that proved fatal during the interest rate shock.

However, while bank-level characteristics clearly amplify the social contagion effect, they cannot fully account for the observed deposit dynamics. If the crisis were purely driven by rational depositor responses to fundamental vulnerabilities, we would expect uniform withdrawals across all branches of the same institution, since a bank's balance sheet, capital ratio, and HTM exposure are identical for every branch. Yet, as we show in the next section, deposit outflows varied systematically across branches of the same bank based on their local social exposure. This within-bank heterogeneity suggests that information transmission and local panic played an independent role beyond bank fundamentals, pointing to a distinct social contagion channel that operates even after controlling for all observable and unobservable bank characteristics.

7 Branch-Level Evidence

The previous section established that bank fundamentals amplify social contagion: institutions with high uninsured deposit ratios and large HTM portfolios suffered disproportionate outflows in socially connected regions. However, a critical question remains: *Is the observed deposit flight purely a rational response to bank-level vulnerabilities, or does social transmission generate panic that operates independently of fundamentals?*

To isolate the role of social networks from bank-level fundamentals, we now turn to branch-level analysis. The key insight is that all branches of the same bank share identical balance sheets, capital ratios, HTM exposures, and management quality. If deposit outflows were driven solely by rational assessment of bank fundamentals, we would expect uniform withdrawals across all branches of a given institution. However, if social networks transmit information and sentiment that trigger *local panic*, we should observe heterogeneous deposit flows across branches based on their specific social exposure to the crisis epicenter, even after controlling for all bank-level characteristics.

By exploiting within-bank variation and controlling for bank$\times$time fixed effects, we can hold constant all bank-specific factors and focus exclusively on how local social connectedness shapes depositor behavior. This identification strategy allows us to distinguish between two competing mechanisms: (1) rational screening based on fundamentals versus (2) socially-driven panic that operates beyond fundamentals.

7.1 Within-Bank Variation

Table 4 reports the estimation results of Equation 3. The inclusion of bank×year fixed effects absorbs any shocks common to all branches of the same institution, ensuring that our estimates capture purely local, social-network-driven variation in depositor behavior.

[Insert Table 4 here]

The results provide compelling evidence of social panic operating beyond fundamentals. Branches located in counties with high social exposure to the failed banks experienced a sharp contraction in funding relative to unconnected branches *of the same bank*. Specifically, heavily connected branches saw their deposit growth decline by approximately 2.67 percentage points following the March 2023 crisis (Column 5). This magnitude represents an economically meaningful retrenchment, suggesting that local depositors, alerted by their social networks, actively withdrew funds even when their bank's overall financial condition was identical to that of branches in less-connected regions.

Crucially, this contagion appears distinct from physical proximity. In the same specification, the estimated coefficient on geographic closeness ($LowGeo \times Post$) is positive and statistically significant, indicating that branches in geographically proximate counties actually experienced *higher* deposit growth relative to distant branches of the same bank. This counterintuitive result suggests that physical proximity did not propagate the bank run; if anything, local relationship ties may have provided a stabilizing buffer. The contagion instead leaped across the country through digital social ties, with information traveling along the lines of friendship and family networks and triggering withdrawals in socially connected regions regardless of their physical distance from Silicon Valley or New York.

We rigorously validate this interpretation using spatial placebo tests. By randomly reassigning the treatment status across counties 500 times, we confirm that our estimated treatment effect (magnitude of -3.39) falls in the extreme tail of the empirical distribution ($p < 0.001$). This falsification exercise reinforces that the observed deposit flight is uniquely tied to the actual structure of social networks, rather than spurious spatial correlations or unobserved regional shocks.

The temporal dynamics further support a causal interpretation. Table 5 presents an event study analysis that traces the evolution of deposit growth.

[Insert Table 5 here]

In the period leading up to the crisis ($T-2$), connected and unconnected branches followed parallel trajectories, mitigating concerns about pre-existing differential trends. However, coincident with the bank failures in March 2023 ($T0$), the trend breaks sharply: connected branches suffered an immediate **3.37 percentage point** drop relative to the control group. This sudden divergence confirms that the withdrawal behavior was triggered by the shock itself and propagated rapidly through social channels.

The within-bank identification is critical for our interpretation. Because we control for bank×time fixed effects, the observed heterogeneity cannot be attributed to differences in bank quality, business models, or management decisions. Instead, it reflects the independent effect of local social networks in transmitting information and sentiment that trigger panic-driven withdrawals. This finding establishes that social contagion operates as a distinct channel beyond rational fundamental-based screening.

The branch-level evidence paints a clear picture of the 2023 crisis mechanism. The shock triggered a panic that propagated through social networks, bypassing geographic boundaries and operating independently of bank fundamentals. The within-bank variation demonstrates that social networks generate panic beyond what fundamentals alone would predict. Two branches of the same bank, with identical balance sheets, identical management, and identical regulatory oversight, experience dramatically different deposit flows based solely on their local social exposure. This divergence reveals that social transmission amplifies and accelerates the diffusion of information in ways that pure fundamental analysis cannot capture, creating a distinct contagion channel with important implications for financial stability.

8 Deposit Reallocation

Having established that social networks transmitted both fundamental concerns and panic-driven runs, we now examine the composition and destination of these deposit flows. Understanding *which* deposits fled and *where* they went is crucial for assessing the systemic implications of social contagion. We document three key patterns: (1) a flight-to-safety from uninsured to insured deposits within affected regions, (2) a reallocation across bank size categories, with mid-sized banks bearing the brunt of outflows while community banks and systemically important institutions remain insulated, and (3) heterogeneous responses across different types of failed institutions, reflecting the distinct client bases and information networks associated with each failure.

8.1 Uninsured versus Insured Deposits

The aggregate decline in deposits documented in Section 5 masks a profound recomposition of bank liability structures. If social networks transmit information about bank fragility, we should expect sophisticated depositors to flee, while risk-averse retail depositors might seek safety. Table 6 disentangles these flows, revealing a striking dual pattern.

[Insert Table 6 here]

8.1.1 The Run on Uninsured Deposits

The crisis manifests clearly as a run by uninsured depositors. As shown in Column (2), banks in socially connected regions suffered a dramatic contraction in uninsured deposits, with magnitudes more than double the effect on total deposits. This aligns with the "run motive": large depositors, alert to the specific risks revealed by the SVB collapse (i.e., the danger of holding balances above the $250,000 FDIC limit), utilized social information to identify and exit potentially vulnerable positions.

The mechanism is straightforward but powerful. Uninsured depositors bear direct downside risk in the event of bank failure. When social networks transmitted news of SVB's collapse, driven by unrealized securities losses and a concentrated uninsured deposit base, sophisticated depositors in connected regions immediately recognized the parallel risks at their own institutions. This triggered a rational, self-interested withdrawal of uninsured funds as depositors sought to reduce their exposure below the insurance threshold or move funds to institutions perceived as safer.

Figure 3 confirms the dynamic nature of this run, showing that the divergence in uninsured deposits accelerated immediately post-crisis and persisted for several quarters.

[Insert Figure 3 here]

The speed and persistence of the outflow underscore the efficiency of social networks in transmitting actionable information: within days of SVB's failure, depositors across the country had reassessed their exposure and initiated withdrawals.

8.1.2 The Flight to Safety: Inflows of Insured Deposits

Simultaneously, we document a "flight-to-safety" taking place within the very same affected regions. Column (3) reveals that socially connected banks actually experienced a significant *inflow* of insured deposits. This contrasting pattern illuminates the dual function of social networks during financial turmoil. While they propagate panic among large depositors, they also disseminate awareness of deposit insurance protections to retail savers.

This inflow reflects a rational reallocation by smaller depositors who, alerted to banking sector risks through their social networks, chose to move funds into insured accounts rather than exit the banking system entirely. The FDIC's $250,000 insurance limit provides a credible guarantee, and social information appears to have heightened awareness of this protection. Consequently, rather than fleeing to cash or money market funds, retail depositors reallocated funds into insured accounts, partially mitigating the liquidity shock from the wholesale run on uninsured deposits.

The coexistence of uninsured outflows and insured inflows within the same banks reveals the heterogeneous impact of social contagion across depositor types. Sophisticated, large-balance depositors respond to social signals by reducing exposure, while smaller, retail depositors respond by seeking the safety of insured accounts. This compositional shift has important implications for bank funding stability: while total deposits may decline only modestly, the loss of uninsured deposits represents a more severe liquidity shock, as these funds are typically more concentrated and more prone to sudden withdrawal.

8.2 Reallocation across Bank Size

The flight-to-safety documented above operates not only across deposit types but also across bank size categories. If social networks transmit information about bank fragility, the response should depend on depositors' incentives to run, and these incentives vary systematically with bank size. We test this mechanism by examining heterogeneity across bank sizes, categorizing institutions by their total assets. As illustrated in Figure A.5, bank size serves as a potent proxy for the structural friction between insured retail funding and uninsured corporate funding, as well as for the implicit safety net provided by "too-big-to-fail" perceptions.

Table 7 reveals a striking non-monotonic pattern that illuminates where social panic translates into actual runs.

[Insert Table 7 here]

For the smallest institutions (Small Community Banks, Columns 1–2), social connectedness had no discernible impact on deposit flows. These banks, protected by high levels of FDIC insurance and deep relationship ties, remained insulated from the panic. Their depositors, facing essentially zero loss risk, had no economic incentive to react to the distress signals circulating in their social networks. The null result here confirms that pure information transmission is insufficient to trigger a run without a corresponding pecuniary incentive.

In sharp contrast, the epicenter of the social run was located in the mid-sized banking sector (Column 3). These institutions, often possessing significant uninsured liabilities but lacking the implicit "too-big-to-fail" guarantee, faced the most severe penalty. For these banks, high social exposure translated into a large and significant contraction in deposit growth. This suggests that the "social run" was highly rational: it targeted the specific segment of the banking system where the risk of loss was real and the safety net was uncertain. Mid-sized banks occupy a precarious middle ground: large enough to attract uninsured corporate deposits, but small enough to be perceived as vulnerable to failure.

As bank size increases further to Systemically Important Banks (Columns 4–5), the negative effect of social connections attenuates. While the largest banks still faced pressure from socially transmitted sentiment, the magnitude of the outflow was dampened relative to mid-sized peers. This likely reflects the stabilizing force of the "too-big-to-fail" perception, which reassured depositors that their funds remained safe despite the swirling panic, thereby blunting the impulse to run. The implicit government guarantee acts as a firewall against social contagion, preventing information transmission from translating into destabilizing withdrawals.

This non-monotonic pattern, insulation at the bottom, severe outflows in the middle, and attenuation at the top, mirrors the uninsured-versus-insured reallocation documented above. Together, they reveal a coherent picture: social contagion drives deposits away from vulnerable mid-sized banks with high uninsured exposure, channeling them toward either insured accounts or institutions perceived as too big to fail. The reallocation is not random but follows the contours of deposit insurance coverage and implicit government guarantees.

8.3 Heterogeneity by Failed Institution

Did all failures spark the same contagion? In Table A.2, we decompose the effect by specific failed institution, revealing important heterogeneity that reflects the distinct client bases and information networks associated with each bank.

Social connectedness to Silicon Valley Bank (*SVBSCI*) and Signature Bank (*SIBSCI*), institutions serving specialized, highly networked communities in tech and crypto, strongly predicts deposit outflows. These banks catered to specific industries characterized by dense social and professional networks. When they failed, information spread rapidly through these tight-knit communities, triggering contagion to other banks serving similar clients or located in regions with strong social ties to Silicon Valley and New York's tech/crypto hubs.

Conversely, contagion from First Republic Bank (*FRBSCI*) appears partly geographic, consistent with its business model as a regional wealth management bank. FRB's client base was more geographically concentrated and less defined by industry-specific networks. As a result, the transmission of distress signals followed both social and geographic channels, with physical proximity playing a more prominent role than in the SVB and SIB cases.

This nuance highlights that social contagion is most potent when the failed institution is embedded in a specific, information-dense community (like the tech sector) rather than a general geographic market. Industry-specific networks appear to transmit information more efficiently than purely geographic ties, suggesting that the structure and density of social connections matter for the speed and scope of contagion.

8.4 Implications for Financial Stability

The deposit reallocation patterns documented in this section carry important implications for financial stability policy. First, the flight from uninsured to insured deposits suggests that deposit insurance remains a credible and effective tool for stabilizing retail funding, even in the age of digital banking and social media. However, the simultaneous run on uninsured deposits underscores the fragility of wholesale funding, particularly for banks serving concentrated, highly networked client bases.

Second, the heterogeneity across failed institutions implies that contagion risk is not uniform across the banking system. Banks embedded in dense social or professional networks, such as those serving the tech industry, crypto sector, or other specialized communities, face heightened vulnerability to socially-transmitted runs. Regulators may need to consider network structure and client base composition as additional dimensions of systemic risk, beyond traditional balance-sheet metrics.

Finally, the speed and efficiency of social transmission observed during the 2023 crisis suggest that traditional crisis management tools may be less effective in the digital age. By the time regulators recognize and respond to emerging stress, social networks may have already propagated panic across the system, triggering withdrawals that outpace policy interventions. This underscores the need for real-time monitoring of social sentiment and proactive communication strategies to counter misinformation and panic.

9 Real Economic Consequences

The preceding sections establish that social networks transmitted deposit shocks during the 2023 banking crisis, generating both rational responses to fundamental vulnerabilities and panic-driven runs that operated independently of bank balance sheets. A natural question follows: *Did these liability-side shocks have real economic consequences, or were they merely financial reshuffling with no impact on credit supply and economic activity?*

This section examines the transmission of socially-driven deposit shocks to the real economy through the credit supply channel. Our central hypothesis is that banks experiencing deposit flight due to social contagion will respond by contracting credit supply to preserve liquidity buffers and maintain regulatory capital ratios. We test this hypothesis by analyzing two major credit markets, small business lending and mortgage lending, where banks play a dominant role as intermediaries. If social contagion merely redistributed deposits across banks without affecting aggregate credit supply, we should observe no differential lending patterns. However, if deposit shocks constrain bank lending capacity, we should observe credit contractions concentrated in regions with high social exposure to the crisis.

The analysis proceeds in two steps. First, we examine small business lending using Community Reinvestment Act (CRA) data, which captures loans to small firms, a segment particularly dependent on bank credit and vulnerable to credit supply shocks. Second, we analyze mortgage lending using Home Mortgage Disclosure Act (HMDA) data, focusing on the residential real estate market where credit availability directly affects household wealth and consumption. For both markets, we employ Poisson pseudo-maximum likelihood estimation to account for the skewed distribution of lending volumes and the presence of zero-lending observations.

9.1 Small Business Lending

Table 8 reports the Poisson pseudo-maximum likelihood (PPML) estimates for small business lending, examining both total loan amounts (intensive margin) and the number of originations (extensive margin).

[Insert Table 8 here]

The results provide clear evidence that socially-transmitted deposit shocks translated into credit supply contractions for small firms.

Consistent with the liquidity management hypothesis, the PPML coefficient on $HighSCI \times Post$ for total loan amounts is -0.029 (Column 1), implying a contraction of approximately $e^{-0.029} - 1 \approx -2.9\%$ relative to unexposed counties within the same institution. This retrenchment reflects a precautionary response: banks facing socially-driven deposit volatility prioritize internal liquidity over new credit extension. The contraction is even more pronounced at the extensive margin: the coefficient of -0.051 on *CRcnt* (Column 2) implies a $e^{-0.051} - 1 \approx -5.0\%$ decline in new originations, suggesting that banks tightened approval standards and reduced lending relationships rather than merely scaling back loan sizes.

Interestingly, the small business market exhibits a distinct sensitivity pattern compared to our baseline deposit results. While social connections dominated in explaining deposit flows, here physical proximity exerts a larger effect on credit supply. The PPML coefficients on $LowGeo \times Post$ imply that geographically proximate regions experienced a 4.7% reduction in lending volumes ($e^{-0.048} - 1$) and an 8.8% decline in loan counts ($e^{-0.092} - 1$), outweighing the social contagion channel.

This reversal is economically meaningful and reveals an important asymmetry in transmission mechanisms. While social networks efficiently transmit information about bank fragility across geographic space, triggering deposit withdrawals in distant but socially connected regions, the transmission to small business credit appears more constrained by local economic conditions and relationship-specific factors. Small business lending relies heavily on soft information, local market knowledge, and long-term relationships between banks and borrowers. When banks face funding shocks, they may prioritize maintaining lending relationships in their core geographic markets while cutting back more aggressively in socially connected but geographically distant regions where relationship ties are weaker.

Nevertheless, the significant contraction driven by social connectedness confirms that digital contagion still impairs credit access for small firms, even if the magnitude is smaller than the geographic effect. This finding has important implications for regional economic resilience: communities with strong social ties to crisis epicenters may experience credit supply shocks even when their local banks are geographically distant and have no direct exposure to the failed institutions.

9.2 Mortgage Lending

We next turn to the mortgage market, where the standardized nature of underwriting and the prevalence of securitization might lead to different transmission dynamics. Table 9 presents the results, revealing a severe contraction in housing credit that far exceeds the small business lending effects.

[Insert Table 9 here]

The PPML coefficient on $HighSCI \times Post$ for mortgage loan amounts is -0.220 (Column 1). Since PPML estimates a multiplicative model for the conditional mean, this coefficient represents a *proportional* (relative) change rather than an absolute percentage-point shift. Crucially, the inclusion of bank $\times$ year fixed effects means this estimate compares lending by the *same bank* across counties with high versus low social connectedness to the crisis epicenter: conditional on a bank's overall lending capacity in a given year, branches operating in high-SCI counties contracted mortgage originations by $e^{-0.220} - 1 \approx -19.7\%$ relative to branches of the same institution in low-SCI counties. Similarly, the coefficient of -0.113 on

HMDcnt (Column 2) implies a $e^{-0.113} - 1 \approx -10.7\%$ relative decline in originations within the same bank, confirming that the reduction was driven by a broad-based pullback in lending activity rather than just smaller loan sizes.

Crucially, in the mortgage market, the social transmission channel significantly outweighs the geographic one. The PPML coefficient on $LowGeo \times Post$ for loan amounts is -0.080, implying a 7.7% decline ($e^{-0.080} - 1$), less than half the social contagion effect. This striking difference mirrors our baseline deposit findings and underscores the dominance of the digital channel in modern banking crises.

The differential impact across lending markets, small business versus mortgage, reveals important insights about credit supply transmission mechanisms. The substantially larger mortgage effect is consistent with several well-documented mechanisms in the banking literature.[5]

9.3 Implications for Real Economic Activity

The credit supply contractions documented in this section carry significant implications for real economic activity. The 19.7% within-bank relative decline in mortgage lending in socially connected counties represents a substantial shock to local housing markets, with potential spillovers to construction employment, household wealth, and consumption. Similarly, the 2.9% to 5.0% within-bank contraction in small business lending constrains entrepreneurship, job creation, and local economic growth.

These findings demonstrate that social contagion in the banking sector generates negative externalities that extend far beyond the financial system. Even banks that remain solvent and well-capitalized may curtail lending in response to socially-transmitted deposit volatility, creating credit crunches in regions that have no direct economic exposure to the initial shock. This amplification mechanism, from bank failures in California and New York to

[5] Three channels help explain the differential sensitivity. First, mortgage lending is more arm's-length and standardized, whereas small business credit relies on soft information and relationship-specific investments that create switching costs and make credit supply stickier in the short run (Petersen and Rajan, 1994; Berger et al., 2005; Bolton et al., 2016; Ivashina and Scharfstein, 2010). Second, mortgage loans are long-duration assets that exacerbate maturity mismatch when deposit outflows shorten the liability side, so banks rationally curtail long-term commitments first (Diamond and Dybvig, 1983; Drechsler et al., 2017). Third, social networks directly influence household housing expectations and mortgage leverage decisions (Bailey et al., 2018a, 2019), creating demand-side amplification that reinforces the supply-side contraction.

credit contractions in socially connected regions across the country, highlights the systemic importance of social networks in modern financial crises.

Moreover, the heterogeneous effects across lending markets suggest that policy interventions may need to be tailored to specific credit channels. While liquidity support programs like the Bank Term Funding Program (BTFP) can address immediate funding pressures, they may be insufficient to prevent credit supply contractions if banks remain concerned about deposit volatility. Targeted lending programs or credit guarantees for small businesses and mortgage borrowers in affected regions may be necessary to mitigate the real economic consequences of socially-transmitted financial shocks.

10 Conclusion

This paper provides evidence on the role of social networks in transmitting bank runs during the 2023 U.S. banking crisis. Exploiting the collapse of Silicon Valley Bank and other regional banks as a natural experiment, we document that social connectedness, measured by Facebook's Social Connectedness Index, serves as a distinct channel for financial contagion, operating independently of geographic proximity.

Our main findings establish a dual transmission mechanism. First, social networks amplify fundamental vulnerabilities: banks with high uninsured deposit ratios and large held-to-maturity securities portfolios suffer disproportionate outflows in socially connected regions. Second, exploiting within-bank variation reveals that social networks transmit panic beyond fundamentals: deposit flows vary based on local social exposure even after controlling for all bank characteristics. We document a flight-to-safety: uninsured deposits flee while insured deposits flow in. Finally, socially-transmitted deposit shocks lead to significant credit supply contractions, demonstrating real economic consequences.

Our findings carry important implications for financial regulation. Traditional frameworks focus on bank fundamentals, interbank exposures, and geographic clustering. Our results suggest regulators should also monitor social network structures connecting depositor bases across institutions. The speed at which information spreads through social networks, as evidenced by SVB's collapse within 48 hours, underscores the need for rapid policy responses during banking stress. The heterogeneous effects across deposit types also reinforce the stabilizing role of deposit insurance: while uninsured deposits prove highly sensitive to social information, insured deposits exhibit countervailing inflows.

In conclusion, our study demonstrates that social networks constitute a first-order determinant of bank run dynamics in the modern financial system. As digital communication continues to accelerate information transmission, understanding and monitoring these network channels will be essential for maintaining financial stability.

Tables and Figures

Figure 1. Average SC Index of Failed Banks

This figure illustrates the geographic distribution of average social connectedness (SC) between each county and the headquarters counties of failed banks during the 2023 banking crisis (Silicon Valley Bank in Santa Clara County, CA; Signature Bank in New York County, NY; Silvergate Bank in San Diego County, CA; and First Republic Bank in San Francisco County, CA). Darker colors indicate stronger social connections between a given county and the average of these four headquarters counties. The social connectedness index is based on Facebook friendship links between counties, as developed by Bailey et al. (2018a).

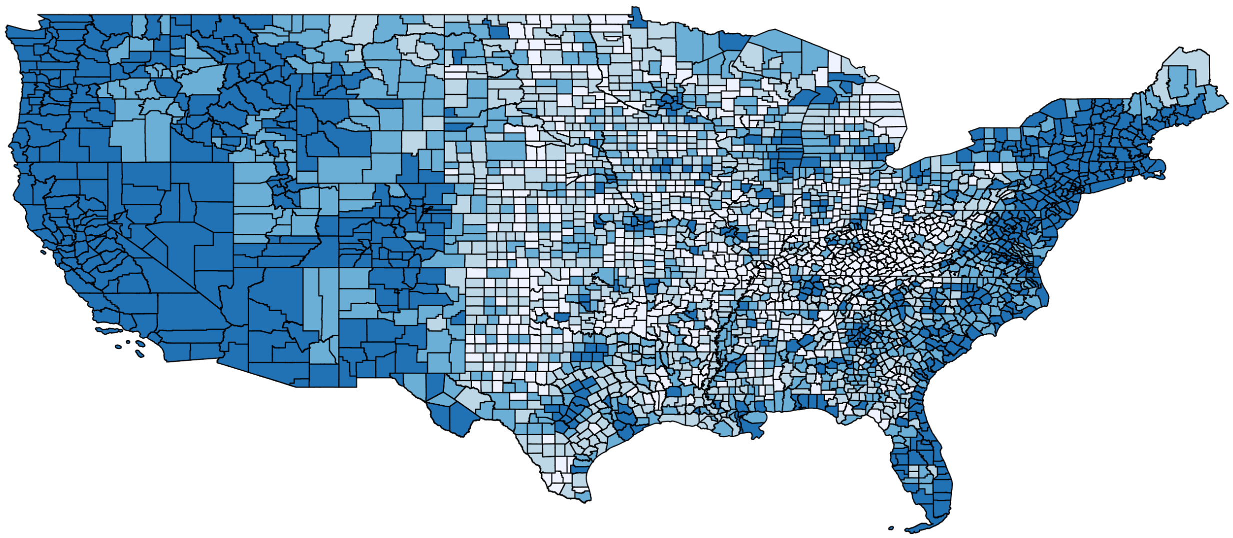

Figure 2. Event Study Analysis of Social Connectedness Effects on Deposit Growth

This figure presents the results of an event study analysis examining the dynamic effects of social connectedness on deposit growth before and after the bank failures in March 2023. The plot displays the estimated coefficients and 95% confidence intervals for the interactions between *HighSCI* (high social connectedness to failed banks' headquarters counties) and time indicators for each quarter relative to the failure events, with Q4 2022 serving as the reference period (normalized to zero). The x-axis represents quarters relative to the banking crisis, with negative values indicating pre-crisis periods and positive values indicating post-crisis periods. The y-axis shows the estimated effect on deposit growth.

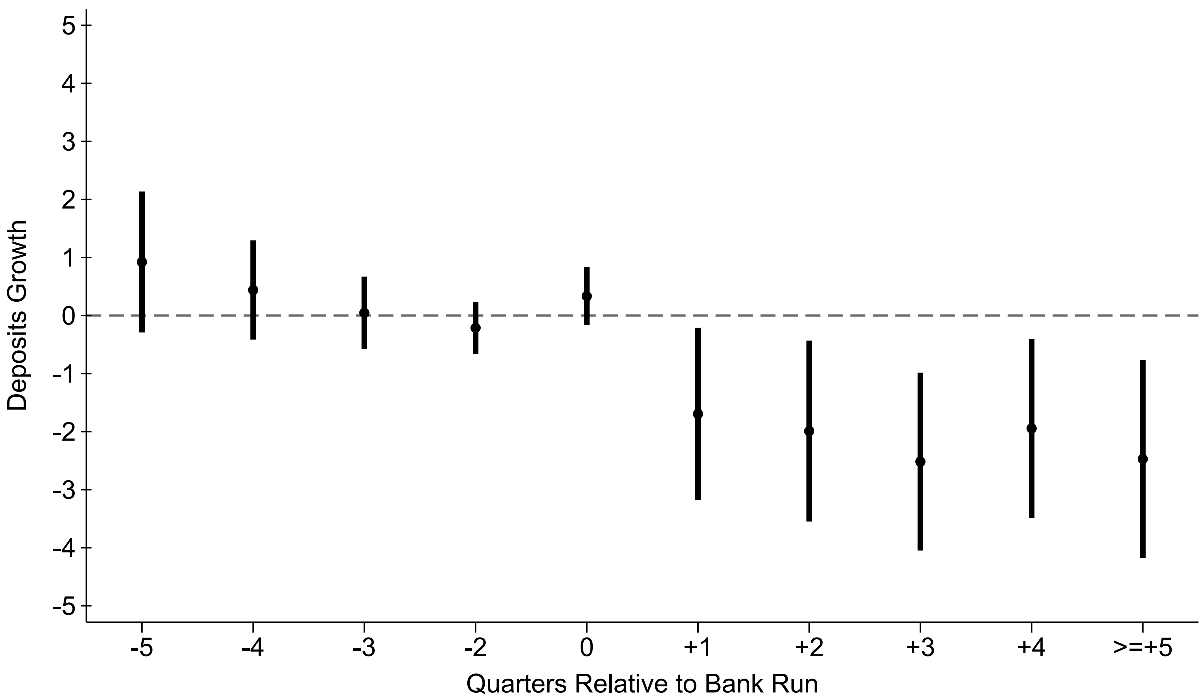

Figure 3. Event Study Analysis of Social Connectedness Effects on Uninsured Deposit Growth

This figure presents an event study analysis of the dynamic effects of social connectedness on uninsured deposit growth around the March 2023 banking crisis. The plot shows estimated coefficients and 95% confidence intervals for the interaction between *HighSCI* (counties with strong social ties to failed banks' headquarters counties) and quarterly time indicators, with Q4 2022 as the reference period (normalized to zero). The x-axis marks quarters relative to the crisis (negative values = pre-crisis; positive = post-crisis), while the y-axis measures the estimated effect on uninsured deposit growth rates.

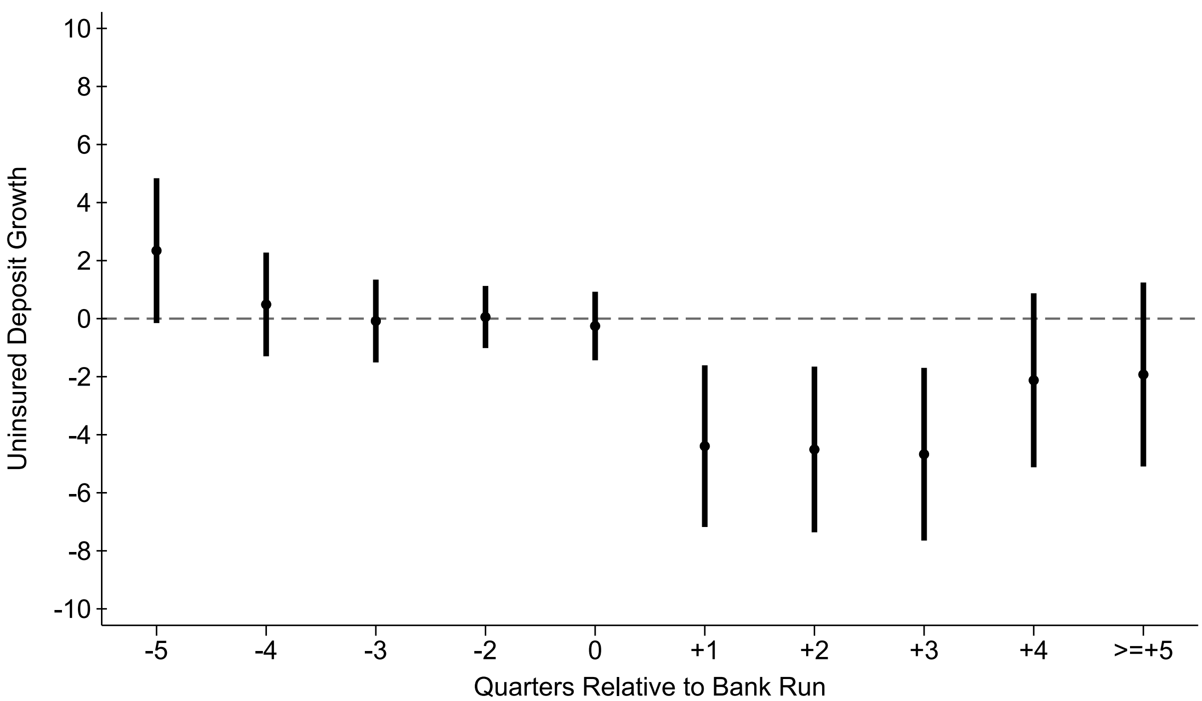

Table 1. Summary Statistics

This table presents summary statistics for key variables used in our analysis. Panel A reports statistics for county-level social connection and geographic distance measures. Panel B presents county/state-year level demographic and economic characteristics. Panel C reports bank-level financial characteristics obtained from Call Reports, including measures of size, capital structure, profitability, and risk. Panel D presents the branch-level annual deposit growth rate from Summary of Deposits (SOD). All continuous variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers.

	Count	Mean	SD	Min	Max
Panel A: County Level					
HighSCI	150756	0.557	0.497	0.000	1.000
LowGeo	150756	0.390	0.488	0.000	1.000
Panel B: County/State-Year Level					
Male	149689	0.495	0.006	0.483	0.513
White	149689	0.721	0.120	0.389	0.914
College	149689	0.420	0.036	0.345	0.504
PopGr	143919	0.290	11.533	-82.744	510.738
GDPGr	149689	3.403	8.870	-22.507	37.186
LnWage	149689	10.807	0.240	10.362	11.650
Panel C: Bank-Year-Quarter Level					
DepGr	128210	7.468	11.913	-17.983	58.905
Size	152970	12.617	1.443	9.668	17.546
LTA	152964	0.625	0.185	0.000	0.919
DTA	152858	0.835	0.127	0.000	0.982
EQA	152970	0.124	0.099	0.039	0.869
NIIR	153272	0.170	0.161	0.000	0.980
CIR	153271	0.684	0.176	0.283	1.425
UDR	85710	0.392	0.154	0.084	0.900
ROE	150690	9.721	8.907	-49.456	37.740
ROA	150690	1.066	1.086	-4.062	6.838
NPL	148353	0.009	0.015	0.000	1.000
CAR	150747	0.123	0.100	-0.124	1.000
Transp	94245	0.347	0.450	-4.724	1.000
Illiq	152857	0.057	0.157	-0.388	0.355
UDepGr	127799	0.111	0.223	-0.480	0.872
Panel D: Branch-Year Level					
BDepGr	296191	6.553	21.642	-46.932	104.020

Table 2. Social Connectedness on Bank Deposit Growth during Bank Runs: Bank-Level

This table presents the relationship between social connectedness, geographical distance, and deposit growth during bank runs. The dependent variable is the year-over-year logarithmic growth rate of quarterly deposits. The sample consists of quarterly bank-county level observations from 2020Q1 to 2024Q2. The Post indicator equals one for periods after March 2023, when the bank runs had already occurred. *HighSCI* and *LowGeo* are binary variables based on median splits: *HighSCI* equals one if a county's social connectedness to counties where failed banks had their headquarters is above the sample median, while *LowGeo* equals one if a county's geographic distance to failed banks' headquarters counties is below the sample median. *Covid* is measured as the ratio of new COVID-19 cases to population in each county for each quarter as a proxy for pandemic severity. ΔMP captures the quarterly change in the Federal Funds rate. Column (1) presents the baseline specification with bank, county, and time fixed effects. Column (2) adds control variables at both the county level (*Male*, *White*, *College*, *PopGr*, *GDPGr*, and *LnWage*) and the bank level (*Size*, *LTA*, *EQA*, *Illiq*, and *ROA*). Column (3) extends the specification in Column (2) by including interactions with the *Covid* variable. Column (4) augments the specification in Column (2) by adding interactions with ΔMP. Column (5) presents the full model with all controls and interaction terms. Column (6) replicates Column (5) but employs two-way clustering at both county and time levels instead of clustering at the county level only. Standard errors are clustered at the county level, with t-statistics shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dep. var =	*DepGr*					
	(1)	(2)	(3)	(4)	(5)	(6)
HighSCI × *Post*	-1.409***	-1.527***	-2.310***	-1.351***	-1.981***	-1.981**
	(-4.34)	(-4.60)	(-6.25)	(-4.11)	(-5.43)	(-2.67)
LowGeo × *Post*	-0.290	-0.220	-0.233	-0.217	-0.337	-0.337
	(-0.86)	(-0.61)	(-0.57)	(-0.61)	(-0.84)	(-0.75)
Covid × *HighSCI*			-0.091***		-0.061***	-0.061
			(-7.06)		(-4.54)	(-1.60)
Covid × *LowGeo*			-0.001		-0.012	-0.012
			(-0.11)		(-0.85)	(-0.66)
HighSCI × ΔMP				-1.216***	-0.710***	-0.710*
				(-8.87)	(-5.69)	(-1.87)
LowGeo × ΔMP				0.071	0.250**	0.250
				(0.49)	(1.98)	(1.33)
Male		188.067**	178.070**	183.544**	177.321**	177.321

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Table 2 – *Continued from previous page*

Dep. var	*DepGr*					
	(1)	(2)	(3)	(4)	(5)	(6)
		(2.49)	(2.35)	(2.45)	(2.34)	(1.53)
White		-10.096	-18.049	-15.357	-18.078	-18.078
		(-0.53)	(-0.94)	(-0.82)	(-0.94)	(-0.79)
College		57.962**	69.461***	53.082**	67.277***	67.277**
		(2.36)	(2.76)	(2.14)	(2.65)	(2.45)
PopGr		0.012***	0.012***	0.011***	0.012***	0.012**
		(2.77)	(2.74)	(2.61)	(2.67)	(2.15)
GDPGr		-0.106***	-0.099***	-0.096***	-0.097***	-0.097***
		(-5.35)	(-4.78)	(-4.82)	(-4.69)	(-4.44)
Size		19.377***	19.584***	19.600***	19.648***	19.648***
		(13.50)	(13.42)	(13.61)	(13.44)	(5.99)
ROE		0.039**	0.037**	0.036**	0.036**	0.036
		(2.29)	(2.17)	(2.12)	(2.12)	(1.42)
ROA		-0.734***	-0.726***	-0.700***	-0.717***	-0.717**
		(-3.71)	(-3.63)	(-3.56)	(-3.59)	(-2.38)
NPL		-38.122***	-38.133***	-36.828***	-37.777***	-37.777***
		(-3.98)	(-3.87)	(-3.87)	(-3.84)	(-4.05)
CAR		-43.750***	-40.869***	-41.955***	-40.501***	-40.501***
		(-6.50)	(-6.17)	(-6.32)	(-6.12)	(-4.13)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.469	0.520	0.523	0.521	0.523	0.523
Observations	85,153	82,863	81,266	82,863	81,266	81,266

Table 3. Moderating Factors in Social Contagion During Bank Runs

This table examines how bank characteristics moderate the relationship between social connectedness and deposit growth during the 2023 banking crisis. The dependent variable is the year-over-year logarithmic growth rate of quarterly deposits. Three bank characteristics are examined as potential moderators: *UDR* (Column 1), *HTM* (Column 2), and *Illiq* (Column 3). *UDR* is dichotomized at the sample median as of Q4 2022, while *HTM* and *Illiq* are dichotomized at the 75th percentile, with banks above the threshold assigned a value of one. Triple interaction terms capture how these characteristics interact with social connections and geographic proximity following the banking crisis. Standard errors are clustered at the county × time level, with t-statistics shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dep. var =	*DepGr*		
Moderator =	*UDR*	*HTM*	*Illiq*
	(1)	(2)	(3)
HighSCI × *Post* × *Moderator*	-1.319***	-1.056***	-0.703*
	(-3.94)	(-2.86)	(-1.81)
LowGeo × *Post* × *Moderator*	1.475***	0.018	3.577***
	(4.44)	(0.05)	(8.58)
Covid × *HighSCI* × *Moderator*	-0.072***	-0.020	-0.006
	(-4.01)	(-1.03)	(-0.27)
Covid × *LowGeo* × *Moderator*	-0.001	-0.017	0.072***
	(-0.03)	(-0.87)	(3.22)
Δ*MP* × *HighSCI* × *Moderator*	-0.494*	0.070	-0.810***
	(-1.89)	(0.23)	(-2.60)
Δ*MP* × *LowGeo* × *Moderator*	0.171	0.455	0.836**
	(0.65)	(1.45)	(2.48)
HighSCI × *Post*	-0.657***	-1.710***	-2.171***
	(-2.90)	(-8.91)	(-11.74)

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Table 3 – *Continued from previous page*

Moderator =	*UDR*	*HTM*	*Illiq*
	(1)	(2)	(3)
Control Variables	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Adjusted R^2	0.537	0.532	0.536
Observations	78,864	78,864	78,864

Table 4. Social Connectedness on Bank Deposit Growth during Bank Runs: Branch-Level

This table presents the relationship between social connectedness, geographical distance, and deposit growth during bank runs. The dependent variable is the annual deposit growth rate. The sample consists of annual branch-level observations from 2021 to 2024, excluding counties where failed banks had branch operations. The Bank Run indicator equals one for periods after 2023. *HighSCI* and *LowGeo* are binary variables based on median splits: *HighSCI* equals one if a county's average social connectedness to counties with failed banks' branches is above the sample median, while *LowGeo* equals one if a county's average geographic distance to counties with failed banks' branches is below the sample median. The COVID Period indicator equals one from 2021 to 2023. ΔMP is measured by the magnitude of Federal Reserve's interest rate changes in each year. Column (1) presents the baseline specification with branch, county, year, and bank × year fixed effects. Column (2) adds control variables at the regional level including *Male*, *White*, *College*, *PopGr*, *GDPGr*, and *LnWage*. Column (3) extends the specification in Column (2) by including interactions with the *Covid* indicator. Column (4) augments the specification in Column (2) by adding interactions with the ΔMP. Column (5) presents the full model with all controls and interaction terms. Standard errors are clustered at the bank level and reported in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dep. var =	*DepGr*				
	(1)	(2)	(3)	(4)	(5)
HighSCI × Post	-3.386***	-3.313***	-2.515***	-2.740***	-2.667***
	(-9.55)	(-9.27)	(-3.15)	(-6.09)	(-3.29)
LowGeo × Post	1.322***	1.348***	2.340**	1.905***	2.221**
	(2.78)	(2.81)	(2.26)	(3.16)	(2.12)
HighSCI × Covid			0.541		0.068
			(1.10)		(0.12)
LowGeo × Covid			0.671		0.297
			(1.18)		(0.43)
HighSCI × ΔMP				-0.331*	-0.315
				(-1.90)	(-1.52)
LowGeo × ΔMP				-0.320	-0.249
				(-1.48)	(-0.96)
GDPGr		-0.074**	-0.068**	-0.069**	-0.068**
		(-2.23)	(-2.05)	(-2.09)	(-2.04)
LnWage		-2.625	-3.873	-3.705	-3.876

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Table 4 – *Continued from previous page*

Dep. var =	*DepGr*				
	(1)	(2)	(3)	(4)	(5)
		(-0.39)	(-0.57)	(-0.55)	(-0.57)
Male		-66.500	-61.815	-62.405	-61.662
		(-0.32)	(-0.30)	(-0.30)	(-0.30)
White		-121.898*	-120.973*	-121.292*	-120.949*
		(-1.69)	(-1.71)	(-1.70)	(-1.71)
College		31.332	36.562	35.177	36.574
		(0.56)	(0.66)	(0.63)	(0.66)
PopGr		0.001	0.001	0.001	0.001
		(0.24)	(0.24)	(0.25)	(0.25)
County FE	Yes	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.208	0.210	0.210	0.210	0.210
Observations	248,954	248,954	248,954	248,954	248,954

Table 5. Dynamic Effects of Social Connectedness on Bank Deposit Growth during Bank Runs: Branch-Level

This table presents the dynamic effects of social connections and geographic distance on deposit growth during bank runs using an event study approach. The dependent variable is the annual deposit growth rate. The sample consists of annual branch-level observations from 2021 to 2024, excluding counties where failed banks had branch operations. The event time T0 corresponds to 2023 (the year of bank failures), T-2 represents 2021, and T+1 represents 2024, with 2022 (T-1) serving as the reference period. *HighSCI* and *LowGeo* are binary variables based on median splits: *HighSCI* equals one if a county's average social connectedness to counties with failed banks' branches is above the sample median, while *LowGeo* equals one if a county's average geographic distance to counties with failed banks' branches is below the sample median. Column (1) presents the baseline specification with branch, county, year, and bank × year fixed effects. Column (2) adds control variables at the regional level including *Male*, *White*, *College*, *PopGr*, *GDPGr*, and *LnWage*. Column (3) extends the specification by including both *Covid* and ΔMP interactions. Column (4) replicates Column (3) but clusters standard errors at the state level instead of the county level. Standard errors are reported in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dep. var =	*DepGr*			
	(1)	(2)	(3)	(4)
HighSCI × T-2	0.618	0.593	0.595	0.595
	(1.30)	(1.21)	(1.21)	(1.21)
HighSCI × T0	-3.392***	-3.365***	-3.365***	-3.365***
	(-7.10)	(-7.01)	(-7.01)	(-3.88)
HighSCI × T+1	-2.695***	-2.718***	-2.722***	-2.722***
	(-6.01)	(-6.02)	(-6.00)	(-3.08)
LowGeo × Post	1.463***	1.416***	2.613***	2.613**
	(3.20)	(3.06)	(2.73)	(2.24)
LowGeo × Covid			0.405	0.405
			(0.66)	(0.58)
LowGeo × ΔMP			-0.348	-0.348
			(-1.47)	(-1.07)
GDPGr		-0.052	-0.051	-0.051
		(-1.58)	(-1.55)	(-1.05)
LnWage		-15.017**	-16.065**	-16.065*

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Table 5 – *Continued from previous page*

Dep. var =	*DepGr*			
	(1)	(2)	(3)	(4)
		(-2.32)	(-2.41)	(-1.82)
Male		-163.918	-163.836	-163.836
		(-0.80)	(-0.81)	(-0.47)
White		-122.770*	-124.834*	-124.834
		(-1.71)	(-1.77)	(-1.31)
College		19.664	32.988	32.988
		(0.36)	(0.62)	(0.29)
PopGr		0.001	0.001	0.001
		(0.28)	(0.28)	(0.25)
County FE	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.216	0.218	0.218	0.218
Observations	285,660	281,010	281,010	281,010

Table 6. Heterogeneity in Deposit Growth During Bank Runs

This table presents the heterogeneous effects of social connectedness on different types of deposit growth during the 2023 banking crisis. The dependent variables are the year-over-year logarithmic growth rates of total deposits (Column 1), uninsured deposits (Column 2), and insured deposits (Column 3). The sample, variables, and fixed effects structure follow the same methodology as in the Table 2. Standard errors are clustered at the county level, with t-statistics shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dep. var =	*DepGr*	*UDepGr*	*IDepGr*
	(1)	(2)	(3)
HighSCI × *Post*	-1.981**	-4.361***	4.187***
	(-2.67)	(-3.18)	(4.99)
LowGeo × *Post*	-0.337	-0.238	0.950
	(-0.75)	(-0.34)	(1.45)
Covid × *HighSCI*	-0.061	-0.189**	0.129**
	(-1.60)	(-2.61)	(2.51)
Covid × *LowGeo*	-0.012	0.027	-0.014
	(-0.66)	(0.92)	(-0.65)
HighSCI × ΔMP	-0.710*	-0.926	-1.288
	(-1.87)	(-1.16)	(-1.44)
LowGeo × ΔMP	0.250	0.124	0.814***
	(1.33)	(0.31)	(3.43)
Male	177.321	85.515	192.202
	(1.53)	(0.35)	(0.82)
White	-18.078	-82.626	-176.068*
	(-0.79)	(-1.71)	(-1.92)
College	67.277**	126.783*	37.163
	(2.45)	(1.84)	(0.62)
PopGr	0.012**	0.013*	0.075
	(2.15)	(1.81)	(1.23)
GDPGr	-0.097***	-0.153***	0.062
	(-4.44)	(-3.31)	(1.57)
Size	19.648***	21.609***	25.725***

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Table 6 – *Continued from previous page*

Dep. var =	*DepGr*	*UDepGr*	*IDepGr*
	(1)	(2)	(3)
	(5.99)	(5.01)	(3.23)
ROE	0.036	0.118**	0.029
	(1.42)	(2.60)	(1.06)
ROA	-0.717**	-0.969*	-1.633***
	(-2.38)	(-1.92)	(-4.66)
NPL	-37.777***	-62.432***	-5.244
	(-4.05)	(-3.71)	(-0.17)
CAR	-40.501***	-67.168***	-8.285
	(-4.13)	(-3.96)	(-0.34)
Bank FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Adjusted R^2	0.523	0.417	0.313
Observations	81,266	81,029	63,033

Table 7. Heterogeneity in Social Contagion Effects Across Bank Size Categories

This table examines how the impact of social connectedness on deposit flows varies across banks of different sizes. Banks are categorized into five size groups based on their total assets as of Q4 2022, with Column (1) representing the smallest banks and Column (5) the largest banks. The dependent variable is the year-over-year logarithmic growth rate of quarterly deposits at the branch level. Standard errors are clustered at the county level, with t-statistics shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dep. var =	*DepGr*				
	Smallest	Small	Medium	Large	Largest
	(1)	(2)	(3)	(4)	(5)
HighSCI × *Post*	-1.673	5.247	-10.265**	-6.592*	-2.483*
	(-0.10)	(0.83)	(-2.22)	(-1.91)	(-1.78)
LowGeo × *Post*	-6.770	7.860	14.809	-16.148**	1.178
	(-0.36)	(0.71)	(1.48)	(-2.30)	(0.93)
HighSCI × *Covid*	-0.005	0.087	-0.073*	-0.037	0.003
	(-0.03)	(1.31)	(-1.65)	(-1.05)	(0.22)
LowGeo × *Covid*	0.056	0.058	0.182**	-0.172***	-0.008
	(0.37)	(0.53)	(2.13)	(-2.86)	(-0.58)
HighSCI × Δ*MP*	2.109	-2.553	1.832	0.402	-0.447
	(0.49)	(-1.62)	(1.61)	(0.49)	(-1.32)
LowGeo × Δ*MP*	-3.119	-2.981	-6.833**	3.444*	-0.259
	(-0.75)	(-0.80)	(-2.18)	(1.68)	(-0.71)
Male	-3982.849	737.470	-3028.343	22.054	-8.142
	(-0.88)	(0.16)	(-1.64)	(0.02)	(-0.04)
White	-2995.016	342.649	-118.835	-228.501	-143.409**
	(-1.15)	(0.77)	(-0.23)	(-0.62)	(-2.02)
College	3034.606	-1067.830	625.392	349.458	35.325
	(1.12)	(-1.14)	(1.62)	(1.12)	(0.62)
PopGr	-0.065***	-0.006***	0.006	0.008***	-0.001
	(-5.91)	(-3.22)	(1.35)	(2.94)	(-0.10)
GDPGr	0.215	-0.073	-0.100	-0.070	-0.071*

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Table 7 – *Continued from previous page*

Dep. var =	*DepGr*				
	Smallest	Small	Medium	Large	Largest
	(1)	(2)	(3)	(4)	(5)
	(1.03)	(-0.96)	(-1.32)	(-1.12)	(-1.78)
County FE	Yes	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.423	0.013	0.100	0.194	0.211
Observations	3,225	9,182	14,903	25,156	192,969

Table 8. Social Contagion Effects on Business Loans (CRA)

This table examines the impact of social contagion on small business lending using data from the Community Reinvestment Act (CRA). The sample consists of bank-county-year level observations aggregated from CRA loan data. The dependent variables are the logarithmic growth rates of total loan amounts (Column 1) and the number of loans originated (Column 2). *HighSCI* and *LowGeo* are binary variables based on median splits: *HighSCI* equals one if a county's social connectedness to counties where failed banks had their headquarters is above the sample median, while *LowGeo* equals one if a county's geographic distance to failed banks' headquarters counties is below the sample median. Post equals one for periods after the 2023 banking crisis. *Covid* is measured as the ratio of new COVID-19 cases to population. ΔMP captures the change in the Federal Funds rate. The specification includes county fixed effects and bank × year fixed effects to control for time-invariant county characteristics and bank-specific time-varying shocks. Standard errors are clustered at the county level, with t-statistics shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dep. var =	*CRamt*	*CRcnt*
	(1)	(2)
HighSCI × *Post*	-0.029**	-0.051***
	(-2.04)	(-4.98)
LowGeo × *Post*	-0.048***	-0.092***
	(-3.07)	(-5.07)
HighSCI × ΔMP	0.025***	0.062***
	(7.09)	(22.90)
LowGeo × ΔMP	0.017**	0.028***
	(2.43)	(3.57)
HighSCI × *Covid*	-0.000**	0.000
	(-2.24)	(1.00)
LowGeo × *Covid*	-0.000*	-0.001***
	(-1.82)	(-4.81)
Covid	0.001**	0.001***
	(2.44)	(4.45)
Controls	Yes	Yes
County FE	Yes	Yes
Bank × Year FE	Yes	Yes

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Table 8 – *Continued from previous page*

Dep. var =	*CRamt*	*CRcnt*
	(1)	(2)
Pseudo R^2	0.553	0.827
Observations	696,172	696,172

Table 9. Social Contagion Effects on Mortgage Loans (HMDA)

This table examines the impact of social contagion on mortgage lending using data from the Home Mortgage Disclosure Act (HMDA). The sample consists of bank-county-year level observations aggregated from HMDA loan-level data. The dependent variables are the logarithmic growth rates of total mortgage loan amounts (Column 1) and the number of mortgage loans originated (Column 2). *HighSCI* and *LowGeo* are binary variables based on median splits: *HighSCI* equals one if a county's social connectedness to counties where failed banks had their headquarters is above the sample median, while *LowGeo* equals one if a county's geographic distance to failed banks' headquarters counties is below the sample median. Post equals one for periods after the 2023 banking crisis. *Covid* is measured as the ratio of new COVID-19 cases to population. ΔMP captures the change in the Federal Funds rate. The specification includes county fixed effects and bank $\times$ year fixed effects to control for time-invariant county characteristics and bank-specific time-varying shocks. All control variables and interaction terms with COVID and monetary policy changes are included. Standard errors are clustered at the county level, with t-statistics shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dep. var =	*HMDamt*	*HMDcnt*
	(1)	(2)
HighSCI × *Post*	-0.220***	-0.113***
	(-12.77)	(-10.85)
LowGeo × *Post*	-0.080***	-0.060***
	(-5.63)	(-5.58)
HighSCI × ΔMP	0.018***	-0.007***
	(4.01)	(-2.73)
LowGeo × ΔMP	-0.007**	-0.014***
	(-2.46)	(-6.49)
HighSCI × *Covid*	-0.001***	-0.001***
	(-8.24)	(-6.44)
LowGeo × *Covid*	-0.001***	-0.000***
	(-3.86)	(-4.42)
Covid	0.002***	0.001***
	(6.42)	(3.62)
Controls	Yes	Yes
County FE	Yes	Yes

Continued on next page

Table 9 – *Continued from previous page*

Dep. var =	*HMDamt*	*HMDcnt*
	(1)	(2)
Bank × Year FE	Yes	Yes
Pseudo R^2	0.611	0.534
Observations	3,162,750	3,162,750

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A Online Appendix of Additional Figures and Tables

Figure A.1. Timeline of the 2023 U.S. Banking Crisis

This figure presents the timeline of the 2023 U.S. banking crisis, from the Federal Reserve's monetary tightening cycle (March 2022–March 2023) through the rapid succession of bank failures in March 2023 (Silvergate, SVB, Signature) and policy responses, culminating in First Republic Bank's seizure in May 2023.

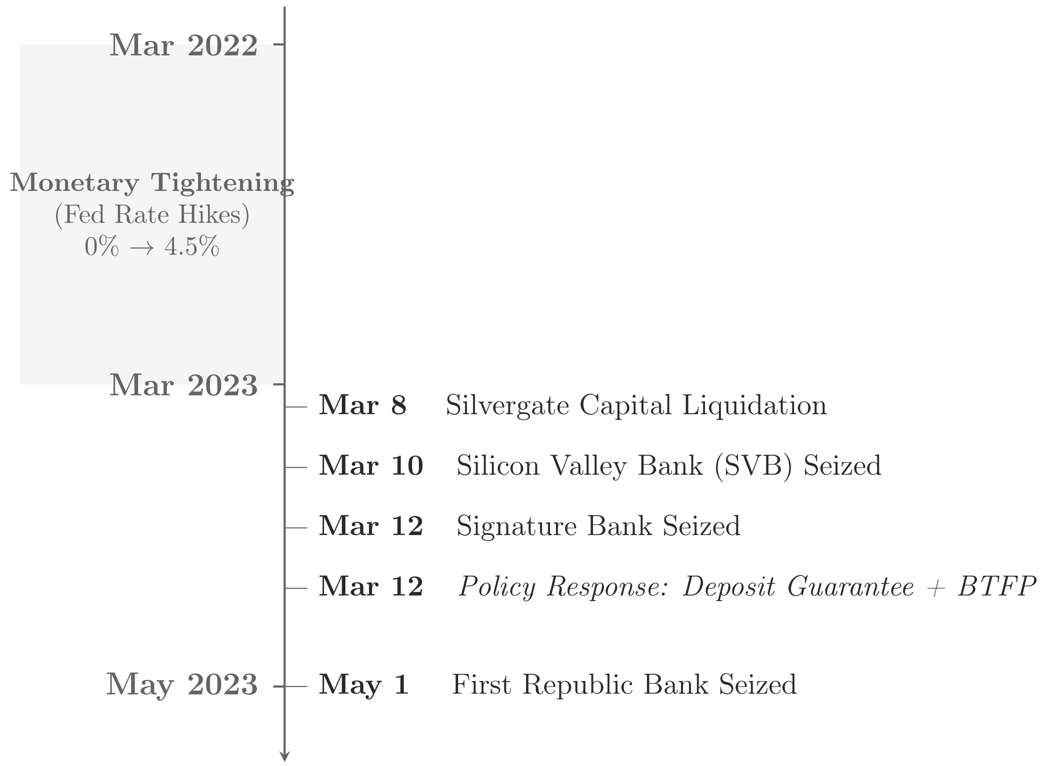
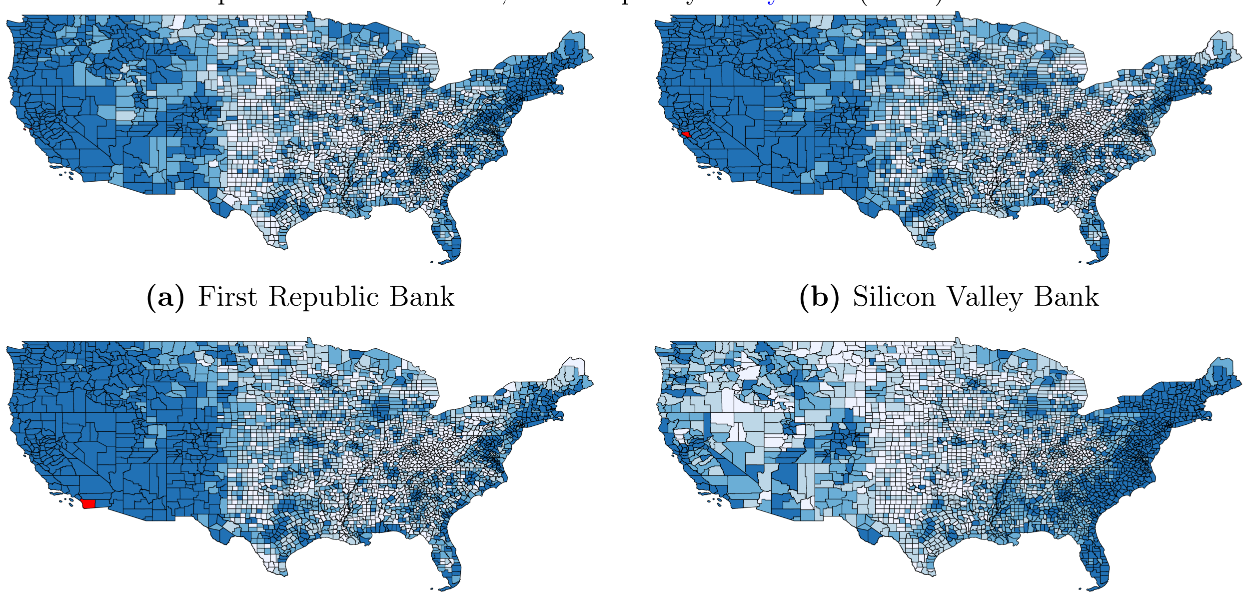


Figure A.2. Social Connectedness Index (SCI) Distribution for Four Failed Banks

This figure presents the geographic distribution of social connectedness for each of the four failed banks individually. Each panel illustrates the Social Connectedness Index (SCI) between U.S. counties and the specific county where each failed bank was headquartered: Panel (a) shows connections to San Francisco County, CA (First Republic Bank); Panel (b) shows connections to Santa Clara County, CA (Silicon Valley Bank); Panel (c) shows connections to New York County, NY (Signature Bank); and Panel (d) shows connections to San Diego County, CA (Silvergate Bank). Darker colors indicate stronger social connections. These visualizations highlight the heterogeneous patterns of social connectedness across different regions of the country to each failed bank's headquarters location, with important implications for the geographical spread of bank run contagion as documented in our analysis. The social connectedness index is based on Facebook friendship links between counties, as developed by Bailey et al. (2018a).



(a) First Republic Bank

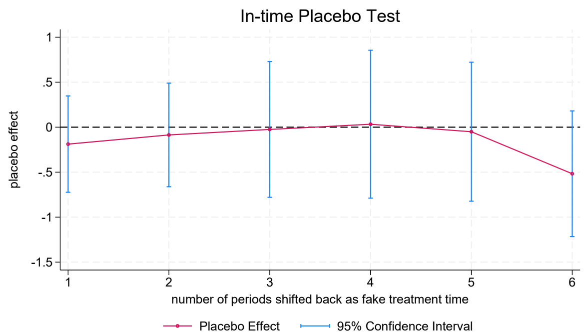
(b) Silicon Valley Bank

(c) Signature Bank

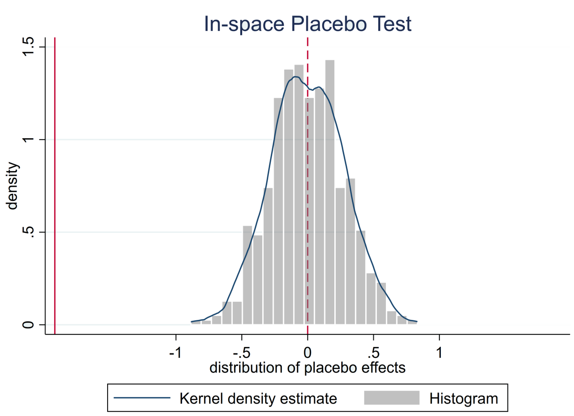
(d) Silvergate Bank

Figure A.3. Placebo Test: Bank-Level

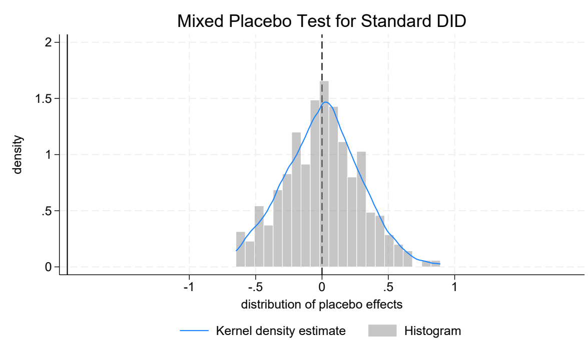
This figure presents the results of placebo tests validating our identification strategy. Panel (a) shows time placebo tests, where we artificially shift the treatment timing backward by 1–6 periods; none yield statistically significant effects, ruling out pre-existing trends. Panel (b) reports spatial placebo tests, with treatment status randomly assigned to counties. Panel (c) combines both approaches (mixed placebo tests).



(a) Time Placebo Test



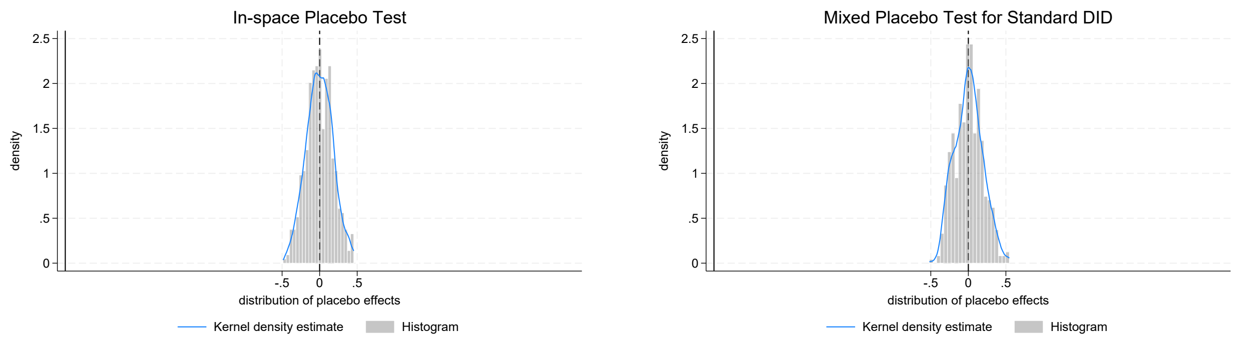
(b) Spatial Placebo Test



(c) Mixed Placebo Test

Figure A.4. Placebo Test: Branch-Level

This figure presents the results of placebo tests validating our branch-level identification strategy. Panel (a) reports spatial placebo tests, where treatment status is randomly assigned to counties; the distribution of placebo estimates confirms that our baseline effect lies in the extreme tail. Panel (b) combines both time and spatial randomization (mixed placebo tests). In both panels, the vertical dashed line indicates the actual estimated coefficient, and the histograms display the distribution of placebo estimates from 500 random permutations.



(a) Spatial Placebo

(b) Mixed Placebo

Figure A.5. Uninsured Deposit Ratios by Asset Quintile (2020-2024)

This figure presents the quarterly evolution of uninsured deposit to total deposit ratios from Q3 2020 to Q2 2024, stratified by bank asset quintiles. The five lines represent banks grouped by asset size quintiles (Q1 = smallest 20% to Q5 = largest 20%), with darker shades indicating larger asset quintiles. The y-axis shows the mean uninsured deposit ratio, while the x-axis marks calendar quarters.

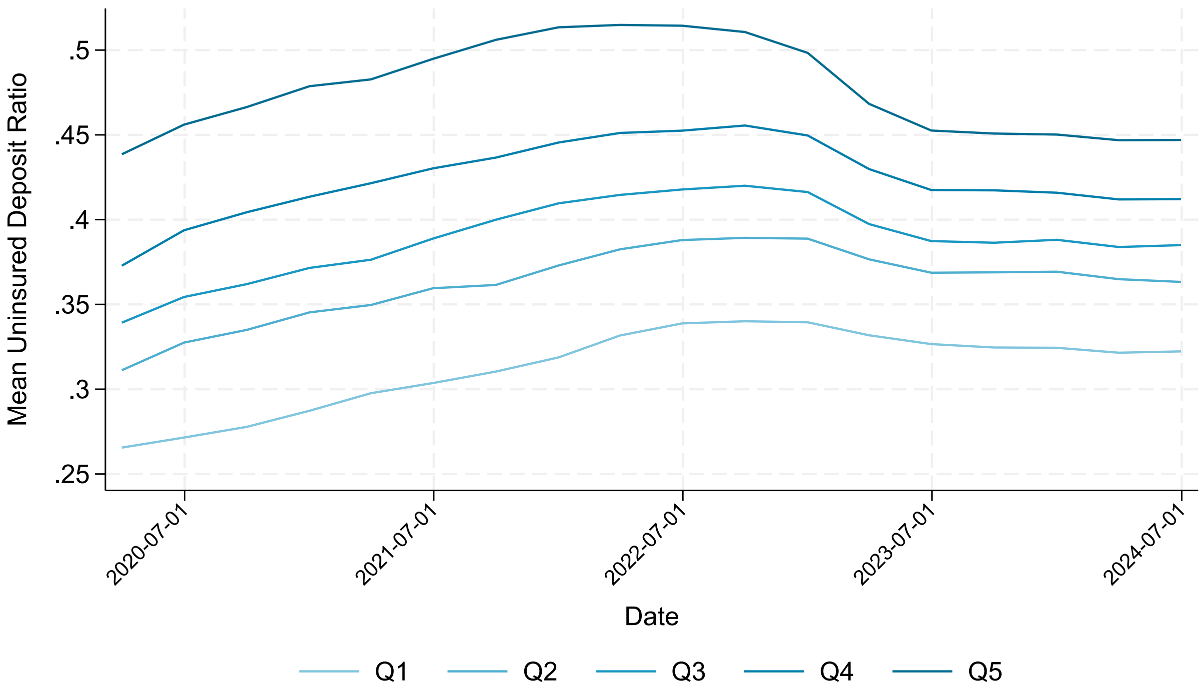


Table A.1. Variable Definitions

Variable	Definition	Source
DepGr	Year-over-year logarithmic growth rate of total deposits in each quarter (bank level) or each year (branch level). Winsorized at the 1st and 99th percentiles.	Call Reports / SOD
UDepGr	Quarterly growth rate of deposits exceeding the $250,000 FDIC insurance limit.	Call Reports
IDepGr	Quarterly growth rate of deposits within the $250,000 FDIC insurance limit.	Call Reports
CRamt	Log growth rate of total small business loan amounts at the bank-county-year level.	CRA
CRcnt	Log growth rate of the number of small business loan originations at the bank-county-year level.	CRA
HMDamt	Log growth rate of total mortgage loan amounts at the bank-county-year level.	HMDA
HMDcnt	Log growth rate of the number of mortgage loan originations at the bank-county-year level.	HMDA
HighSCI	Indicator equal to one if a county's Social Connectedness Index to counties where failed banks were headquartered is above the sample median. $\text{SCI}_{i,j}$ = FB $\text{connections}_{i,j}$ / ($\text{users}_i \times$ users_j), scaled to [1, 10^9].	Meta (Facebook)
LowGeo	Indicator equal to one if a county's geographic distance to failed bank headquarters counties is below the sample median.	NBER County Distance
Post	Indicator equal to one for periods after March 2023 (bank level: quarters after 2023Q1; branch level: years $\geq$ 2023).	—
Covid	Ratio of new COVID-19 cases to population in each county. Measured quarterly (bank level) or annually (branch level).	New York Times

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Table A.1 – *Continued from previous page*

Variable	Definition	Source
ΔMP	Quarterly change in the effective federal funds rate (bank level) or annual change (branch level).	Federal Reserve
Size	Natural log of total assets.	Call Reports
LTA	Total loans divided by total assets.	Call Reports
EQA	Total equity divided by total assets.	Call Reports
ROA	Net income divided by total assets.	Call Reports
ROE	Net income divided by total equity.	Call Reports
NPL	Non-performing loans divided by total loans.	Call Reports
CAR	Regulatory capital divided by risk-weighted assets.	Call Reports
Male	Share of male population in the county.	ACS
White	Share of white population in the county.	ACS
College	Share of population with college education.	ACS
PopGr	Annual population growth rate.	ACS
GDPGr	Annual GDP growth rate at the county level.	BEA / ACS
LnWage	Natural log of average wage in the county.	ACS
UDR	Uninsured deposits divided by total deposits as of 2022Q4. Dichotomized at the sample median for interaction tests.	Call Reports
HTM	Held-to-maturity securities divided by total securities as of 2022Q4. Dichotomized at the 75th percentile.	Call Reports
Illiq	Weighted sum of illiquid and liquid assets scaled by total assets, following Berger and Bouwman (2009). Dichotomized at the 75th percentile.	Call Reports
SVBSCI / *SVBDist*	Natural logarithm of the SCI (or geographic distance) between each county and Santa Clara County, CA (Silicon Valley Bank HQ).	Meta / NBER

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Table A.1 – *Continued from previous page*

Variable	Definition	Source
FRBSCI / *FRBDist*	Natural logarithm of the SCI (or geographic distance) between each county and San Francisco County, CA (First Republic Bank HQ).	Meta / NBER
SGBSCI / *SGBDist*	Natural logarithm of the SCI (or geographic distance) between each county and San Diego County, CA (Silvergate Bank HQ).	Meta / NBER
SIBSCI / *SIBDist*	Natural logarithm of the SCI (or geographic distance) between each county and New York County, NY (Signature Bank HQ).	Meta / NBER

Table A.2. Heterogeneity Analysis: Bank-Specific Social Connectedness Effects

This table presents the bank-specific analysis of social connectedness and geographic distance effects on deposit growth during the 2023 banking crisis. Instead of using binary *HighSCI* and *LowGeo* measures, we employ continuous bank-specific social connectedness measures. For each failed bank, we calculate the natural logarithm of the SCI between each county and the county where the failed bank was headquartered (*SVBSCI*, *FRBSCI*, *SGBSCI*, and *SIBSCI*), as well as the natural logarithm of geographic distance (*SVBDist*, *FRBDist*, *SGBDist*, and *SIBDist*). Columns examine Silicon Valley Bank (*SVBSCI*/*SVBDist*, Column 1), First Republic Bank (*FRBSCI*/*FRBDist*, Column 2), Silvergate Bank (*SGBSCI*/*SGBDist*, Column 3), and Signature Bank (*SIBSCI*/*SIBDist*, Column 4). The results reveal heterogeneous contagion patterns across institutions, likely reflecting differences in business models and client bases. Standard errors are clustered at the county level, with t-statistics shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dep. var =	*DepGr*			
Failed Bank =	SVB	FRB	SGB	SIB
	(1)	(2)	(3)	(4)
BankSCI × *Post*	-1.000***	-0.760***	-1.033***	-2.412***
	(-2.65)	(-2.61)	(-3.08)	(-4.62)
BankDist × *Post*	0.876	1.445**	-1.655***	0.032
	(1.30)	(2.17)	(-3.90)	(0.03)
Covid × *BankSCI*	-0.029**	-0.026***	-0.024**	-0.056***
	(-2.39)	(-2.62)	(-2.33)	(-3.04)
Covid × *BankDist*	0.023	0.031	-0.033**	-0.004
	(1.01)	(1.24)	(-2.25)	(-0.18)
BankSCI × ΔMP	-0.643***	-0.513***	-0.519***	-1.023***
	(-6.05)	(-6.17)	(-5.61)	(-6.26)
BankDist × ΔMP	-0.521***	-0.325*	-0.191*	-0.685***
	(-2.87)	(-1.85)	(-1.72)	(-3.93)
Control Variables	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.523	0.524	0.523	0.524

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Table A.2 – *Continued from previous page*

Failed Bank =	SVB	FRB	SGB	SIB
	(1)	(2)	(3)	(4)
Observations	81,266	81,194	81,266	81,266

Table A.3. Robustness Tests: Alternative Definitions of Social Connectedness

This table presents robustness tests using alternative definitions of social connectedness and distance measures. Each column represents a different definition as indicated in the table header: (1) connections to all three major bank failures in March 2023 (SVB, SGB, and SIB); (2) connections to California-based failures only (SVB and SIB); (3) connections including First Republic Bank along with SVB and SIB; (4) continuous measures using the natural logarithm of average SCI and geographic distance; and (5) using the 75th percentile threshold for defining high social connectedness instead of the median. For columns 1-3 and 5, *HighSCI* and *LowGeo* are binary variables based on the specified failed banks or thresholds. For column 4, the variables represent continuous logarithmic measures. Standard errors are clustered at the county level, with t-statistics shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dep. var =	*DepGr*				
Definition	SVB+SIB +SGB	SVB +SIB	SVB+SIB +FRB	Log Average	75th Pctl
	(1)	(2)	(3)	(4)	(5)
HighSCI × *Post*	-1.945***	-2.106***	-1.935***	-1.137***	-1.774***
	(-5.18)	(-5.99)	(-5.42)	(-3.25)	(-3.49)
LowGeo × *Post*	-0.082	-0.481	1.501	-0.396	-0.203
	(-0.21)	(-1.22)	(1.59)	(-0.37)	(-0.35)
Covid × *HighSCI*	-0.057***	-0.052***	-0.054***	-0.029**	-0.057***
	(-4.22)	(-4.07)	(-4.09)	(-2.47)	(-3.10)
Covid × *LowGeo*	-0.013	-0.021	-0.006	0.039	-0.001
	(-0.93)	(-1.54)	(-0.17)	(1.40)	(-0.06)
HighSCI × ΔMP	-0.718***	-0.706***	-0.552***	-0.585***	-0.992***
	(-5.76)	(-5.68)	(-4.44)	(-6.20)	(-6.72)
LowGeo × ΔMP	0.284**	0.386***	0.957***	-0.770***	0.590***
	(2.22)	(3.07)	(3.41)	(-4.35)	(3.57)
Controls	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.523	0.523	0.523	0.531	0.531

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Table A.3 – *Continued from previous page*

Dep. var =	*DepGr*				
	(1)	(2)	(3)	(4)	(5)
Observations	81,266	81,266	81,266	81,266	81,266

Table A.4. Robustness Tests: Alternative Dependent Variables

This table presents robustness tests using alternative dependent variables to measure deposit flows during the 2023 banking crisis. Column (1) uses the absolute change in deposits rather than the growth rate. Column (2) examines deposits relative to total assets, addressing potential concerns about scaling effects. Column (3) employs a binary outcome variable that equals one if a bank experienced non-negative deposit growth and zero otherwise, allowing for examination of the extensive margin of deposit outflows. Across all specifications, the negative effect of social connections on deposits remains significant, confirming the robustness of our findings to alternative measures of deposit movements. Standard errors are clustered at the county level, with t-statistics shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dep. var =	Δ Deposit	Δ Dep/Asset	Non-Neg Dummy
	(1)	(2)	(3)
HighSCI × *Post*	-0.175***	-1.066***	-0.037***
	(-9.98)	(-3.34)	(-3.45)
LowGeo × *Post*	0.019	-0.884***	-0.001
	(0.97)	(-2.71)	(-0.07)
Covid	0.003**	0.133***	0.002**
	(2.44)	(5.12)	(2.28)
Covid × *HighSCI*	-0.005***	-0.057***	-0.003***
	(-5.73)	(-3.74)	(-5.78)
Covid × *LowGeo*	0.001	-0.009	0.000
	(0.75)	(-0.57)	(0.78)
Δ*MP* × *HighSCI*	-0.023**	-0.192	0.044***
	(-2.09)	(-0.84)	(5.39)
Δ*MP* × *LowGeo*	0.029**	0.212	0.018**
	(2.32)	(0.88)	(2.17)
Male	9.095**	110.872	-4.505**
	(2.32)	(1.47)	(-2.22)
White	1.959*	-65.507***	-1.139**
	(1.76)	(-3.80)	(-2.53)
College	0.347	46.670**	1.026
	(0.22)	(2.03)	(1.52)

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Table A.4 – *Continued from previous page*

Dep. var =	Δ Deposit	Δ Dep/Asset	Non-Neg Dummy
	(1)	(2)	(3)
PopGr	0.000	0.004	0.000
	(0.51)	(0.75)	(0.51)
GDPGr	-0.002***	-0.065***	-0.000
	(-3.04)	(-3.40)	(-0.52)
Size	0.136***	-12.469***	0.136***
	(2.63)	(-10.15)	(6.19)
ROE	0.001	-0.035*	0.001**
	(0.67)	(-1.65)	(1.98)
ROA	-0.040***	-0.745***	-0.030***
	(-3.78)	(-2.88)	(-5.48)
NPL	-0.391	-47.254***	-0.686***
	(-0.58)	(-5.44)	(-2.86)
CAR	-2.052***	10.002	-0.778***
	(-4.42)	(1.12)	(-6.13)
Bank FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Adjusted R^2	0.289	0.328	0.110
Observations	81,368	76,584	81,368