DEUTSCHE BUNDESBANK EUROSYSTEM

Discussion Paper

Deutsche Bundesbank
No 41/2026

Beyond local deposit markets: Social spillovers in deposit pricing

Sofia Anyfantaki
(European Central Bank and Bank of Greece)

Panagiotis Avramidis
(Alba Graduate Business School, The American College of Greece)

Natalya Martynova
(Deutsche Bundesbank)

Discussion Papers represent the authors' personal opinions and do not necessarily reflect the views of the Deutsche Bundesbank or the Eurosystem.

Editorial Board: Daniel Foos
Stephan Jank
Thomas Kick
Martin Kliem
Malte Knüppel
Christoph Memmel
Hannah Paule-Paludkiewicz

Deutsche Bundesbank, Wilhelm-Epstein-Straße 14, 60431 Frankfurt am Main,
Postfach 10 06 02, 60006 Frankfurt am Main

Tel +49 69 9566-0

Please address all orders in writing to: Deutsche Bundesbank, Press and Public Relations Division, at the above address or via email: www.bundesbank.de/contact

Internet http://www.bundesbank.de

Reproduction permitted only if source is stated.

DOI https://doi.org/10.71734/DP-2026-41
ISBN 978-3-98848-100-9
ISSN 2941-7503

Beyond local deposit markets: Social spillovers in deposit pricing *

Sofia Anyfantaki† Panagiotis Avramidis‡ Natalya Martynova§

Abstract

Deposit markets are local partly because depositors pay limited attention to rates elsewhere. Our model predicts that social networks make distant rate changes salient, and deposit-rate spillovers increase with social connectedness and depositor sophistication. We test these predictions using merger-driven deposit-rate shocks and county-level digital social connectedness across the US over 2015–2023. The data support both predictions: small banks rates rise following shocks in socially connected but geographically distant counties, while placebo connections show no effect. Deposit rates converge as social connections increase over time, suggesting that digital social networks reshape the geography of deposit-market competition.

Keywords: Social connections, deposit pricing, market segmentation, limited attention

JEL classification: G20; G21; G23; G29

*The views expressed in this paper are those of the authors and may not necessarily represent those of the European Central Bank, Deutsche Bundesbank or the Eurosystem. We would like to thank Adrien d'Avernas, Robert Adams, Kartik Anand, Jennie Bai, Diana Bonfim, Martin Brown, Jennifer Dlugosz (discussant), Sebastian Doerr, Falko Fecht, Andreas Fuster, Livio Stracca and conference participants at the AI RTF mini-workshop (ECB), Winter 2025 IBRN Meeting (Paris), CRETE 2025, III Marvel Workshop (Valencia), IJCB Annual Conference (Bern), and IBEFA Summer Meeting 2026 (Denver) for helpful comments.

†European Central Bank, Directorate General of Research, Financial Research Division, and Bank of Greece, Economic Analysis and Research Department; Email: sofia.anyfantaki@ecb.europa.eu

‡Alba Graduate Business School, The American College of Greece; Email: pavramidis@alba.acg.edu

§Research Center, Bundesbank; Email: natalya.martynova@bundesbank.de

1 Introduction

Deposit markets are local and segmented: limited attention to rates offered by banks elsewhere leaves depositors unresponsive to rate differentials, sustaining banks' market power over their depositor base (Calem & Nakamura 1998, Lu & Wu 2026, Drechsler, Savov & Schnabl 2017). At the same time, households are increasingly exposed to financial developments in geographically distant markets through digital social interactions (Kuchler, Li, Peng, Stroebel & Zhou 2022, Cookson, Mullins & Niessner 2024). Whether such exposure reduces depositor inattention and erodes informational boundaries remains an open question.

We examine how deposit-rate shocks propagate across banking markets through digital social networks. Our central hypothesis is that social ties make outside rate changes salient to otherwise inattentive households, triggering search for better offers.[1] This search increases the sensitivity of each bank's deposit supply to competitors' rates and induces small banks to raise their own rates, even when the original shock occurs in a geographically distant market. Using measures of exposure to merger-driven variation in deposit rates through county-level digital social connectedness, we show that deposit rate shocks transmit across socially connected counties and significantly affect small bank pricing behaviour. Spillovers are economically meaningful, and amplified in financially sophisticated markets.

To formalize the mechanism, we develop a stylized model of deposit-rate competition across socially connected counties. In the model, a deposit-rate increase in county A generates social-media buzz that spreads to county B in proportion to the strength of social connectedness between the two counties. This buzz raises awareness among depositors in B, who initiate search for better rates when the expected benefit exceeds their heterogeneous search cost. The mechanism resembles "wake-up-call" contagion (Ahnert & Bertsch 2022), though here shocks in socially connected markets do not change beliefs about local fundamentals, but make outside rates salient to otherwise inattentive depos-

[1] A complementary study (Zhou 2025) shows that social networks play an important role in making Fintech lending more attractive to uninformed customers.

itors and trigger search. Higher awareness raises the substitutability of deposits across banks and each bank's deposit supply sensitivity to competitors' rates. This induces small banks, who compete à la Bertrand in differentiated products, to raise rates. The model incorporates behavioural frictions such as inattention and heterogeneous search costs, and predicts that social spillovers grow with both social connectedness and the sophistication of households in the receiving markets.

We take these predictions to a county-level panel of US deposit markets over the period 2015–2023. The empirical analysis examines whether deposit-rate changes in one county spill over to socially connected but geographically distant counties. We combine branch-level deposit-rate data from RateWatch with county-pair measures of social connectedness and focus on rates offered by small banks at brick-and-mortar branches, excluding online banks.

We measure digital social proximity using the Social Connectedness Index (SCI) of Bailey, Cao, Kuchler & Stroebel (2018), which captures the intensity of Facebook friendship links between counties. Given Facebook's scale and relative representativeness of its user body, the SCI serves as a useful proxy for real-world social connections (Bailey, Cao, Kuchler, Stroebel & Wong 2018) and has been shown to reflect economically meaningful peer effects in financial decisions (Hu 2022).

Identification exploits merger-driven branch closures by large banks as plausibly exogenous local competitive shocks. We focus on branch closures by large banks involved in mergers within a two-year window, which are unconfounded with local market characteristics (Garmaise & Moskowitz 2006). We validate their role as local competitive shocks to prices by showing that they raise deposit rates among small banks, who compete locally, while leaving large bank rates broadly unchanged.[2]

To examine whether these local shocks spill over through social connections, we construct each focal county's exposure to deposit-rate changes in socially connected counties

[2] The absence of a large bank response is consistent with large banks' uniform pricing strategies and the lower rate sensitivity of their customers. The small bank response is in line with prior work showing that, in local deposit markets dominated by large banks, small banks offer lower deposit rates (d'Avernas, Eisfeldt, Huang, Stanton & Wallace 2023). It follows that a decline in large banks' market power should induce small banks to raise their own rates, while large bank customers remain comparatively rate-insensitive.

by weighting rate changes in peer counties by the strength of their SCI links. This exposure is instrumented with the corresponding SCI-weighted merger-driven large bank branch closures in connected counties. The baseline specification includes county and year fixed effects, controls for time-varying characteristics of the focal area, excludes counties within 25 miles of the focal county and controls separately for geographic and economic proximity (Flynn & Wang 2025), thereby isolating transmission through distant social connections. Our main result is that a one-standard-deviation increase in SCI-weighted exposure to deposit rate changes in socially connected but geographically distant counties raises the focal county's small-bank deposit rates by approximately 19 basis points, an economically sizable effect.

To investigate heterogeneity in transmission, we construct a county-level measure of financial sophistication using principal component analysis on nine variables capturing education and stock-market participation. Spillovers are strongest in counties with high financial sophistication, consistent with the model's prediction that greater financial sophistication strengthens search and local bank responses. This finding is also in line with evidence that financial sophistication reduces banks' market power (Drechsler et al. 2017, Fleckenstein & Longstaff 2024), and is associated with greater digital sophistication (Gambacorta, Gambacorta & Mihet 2023).

To support our interpretation that social networks, rather than confounding factors such as geographic or economic factors, drive these results, we conduct an extensive set of robustness checks. We show that the effect survives when social exposure is restricted to each county's strongest 10% of social ties, holds in the subsample of counties with no large-bank presence, is largely robust to replacing time fixed effects with census-division-by-time fixed effects, and persists when the geographic exclusion radius is widened to 50 miles. Importantly, the effect disappears under a placebo test that reassigns the same SCI weights to socially weakly connected but geographically and economically similar counties, indicating that the baseline result depends on the identity of a county's actual social connections rather than on unobserved regional trends.

Finally, a corollary of our findings is that increased participation in online social

networks reduces spatial fragmentation in deposit markets. Specifically, as social interactions intensify, they reduce local market heterogeneity by making information about rate changes elsewhere more salient, prompting small banks to adjust toward a common equilibrium rate. Using a β-convergence framework (Barro & Sala-i Martin 1992), we test whether initial disparities between a county's deposit rates and the weighted average rates of its socially connected peers diminish as social connectedness increases. We find that social connectivity accelerates the rate of convergence in small bank deposit rates across socially connected counties. This result underscores the role of social networks in harmonizing pricing behaviour especially among smaller banks, which are more sensitive to peer influence and local competitive dynamics than their larger counterparts.

Relation to the literature. Our analysis contributes to three distinct strands of literature. First, our paper contributes to the growing literature on the role of social networks in finance. While classical investment theories assume that investment ideas are transmitted among investors through asset prices and quantities in impersonal markets, recent theoretical and empirical research highlights the role of direct social interactions in shaping economic decision making (e.g., Hong, Kubik & Stein 2004, Shiller 2019, Hirshleifer 2020). Empirical studies have shown that social networks affect a wide range of financial decisions, including home purchases (Bailey, Cao, Kuchler & Stroebel 2018), leverage choices (Bailey, Dávila, Kuchler & Stroebel 2019), product adoption (Bailey, Johnston, Kuchler, Stroebel & Wong 2022) and insurance take-up decisions (Hu 2022). The paper closest to our work is Kuchler et al. (2022), which examines how social proximity to mutual fund capital affects stock liquidity and firm valuation. We build on this literature by providing novel evidence that social networks influence bank competition and deposit pricing strategies, particularly among small banks responding to competitive shocks in socially connected regions.

Second, we add to the emerging literature on the role of online social connections in banking. Recent studies have uncovered how social networks impact banking-related outcomes across regions. For example, Flynn & Wang (2025) find that counties more socially connected to those affected by natural disasters experience increases in bank de-

posits, suggesting that social ties transmit economic shocks. Rehbein & Rother (2025) show that cross-county bank lending intensifies with greater social connectedness, while Zhou (2025) examines how social networks facilitate FinTech lending adoption and refinancing decisions. Our study complements this line of research by exploring a distinct channel: the impact of social proximity on deposit pricing, mediated through changes in local market power.

Beyond the role of social connectedness, our mechanism rests on a growing literature that traces deposit-market power and incomplete pass-through to depositor inattention and limited search (Drechsler et al. 2017, Adams, Hunt, Palmer & Zaliauskas 2021, Egan, Hortaçsu, Kaplan, Sunderam & Yao 2025, Lu & Wu 2026). Lu & Wu (2026) directly show that inattention dampens deposit outflows and weakens pass-through. Closest in mechanism, Eichenbaum, Puglisi, Rebelo & Trabandt (2025) let social interaction govern *when* aggregate attention rises over the interest-rate cycle, generating state-dependent net interest margins and monetary transmission within a single market. We instead ask *where* a localized rate shock becomes salient: bilateral social ties determine which distant markets a shock reaches, so our focus is the cross-market propagation of deposit rates rather than their aggregate cyclical pass-through.

Finally, recent studies have demonstrated that large banks tend to adopt uniform pricing strategies across broad geographic regions, while small banks adjust rates in response to local competitive conditions. For example, d'Avernas et al. (2023) show that large banks face significantly lower demand elasticities for deposit rates and are more likely to operate in markets with less rate-sensitive customers. Begenau & Stafford (2023) find that large banks have a near universal use of uniform deposit rate setting policies. Similarly, Granja & Paixao (2023) demonstrate that US banks price deposits nearly uniformly across branches and that this practice plays a central role in explaining deposit rate dynamics following mergers. Our findings reinforce this body of work by identifying social networks as a novel determinant of local deposit rates and bank pricing power. They also point to a distinct channel for transmitting financial information, one that shapes deposit pricing particularly among small banks.

The remainder of the paper is structured as follows. In Section 2, we describe the model and its main predictions. In Section 3, we describe the data and the construction of key variables. In Section 4, we examine the spillover effects of deposit rate changes across socially connected counties and test alternative explanations. In Section 5, we investigate the role of social connectedness in accelerating mean reversion in deposit-rate gaps between counties and their socially connected peers. In Section 6 we conclude.

2 Mechanism

This section provides a simple framework that describes how a deposit rate shock in a local market can affect deposit pricing in a socially-connected but geographically distant local market. The full model behind our empirical analysis is presented in Appendix A. Here, we outline the relevant economic mechanism and motivate the empirical predictions.

Consider two local markets, A and B. County A, which is our definition of local market, experiences an exogenous increase in deposit rates of size Δr_A. This change might be the result of, for example, a merger-induced branch closure. The shock generates social-media activity of intensity $\mu_A = \alpha w_{BA} \Delta r_A$, where w_{BA} measures the strength of online connections between depositors in markets A and B, and α captures the overall visibility of financial content on the platform. Depositors in county B observe a Poisson number of buzz-related posts with mean μ_A, and become aware of the shock with probability

$$p(w_{BA}, \Delta r_A) = 1 - \exp[-\alpha w_{BA} \Delta r_A].$$

Absent such salient exposure, depositors in county B remain inattentive and do not initiate any search. However, once aware, depositors in county B decide whether to search for better deposit rates. Now, we assume that a share λ of households is financially sophisticated and faces a lower search cost c_L, while the rest face a higher search cost $c_H > c_L$. Active searchers observe and compare all offers, becoming sensitive to rate differences across banks. The endogenous share of active searchers is m.

Banks in county B compete a la Bertrand in differentiated products. Each bank i

attracts a volume of deposits:

$$D_i = a + br_i - d(m)\,\bar{r}_{-i}, \qquad d(m) = d_0 + d_1 m,\ d_1 > 0,$$

increasing in its own posted rate and decreasing in rivals' rates, where $\bar{r}_{-i}$ is the average rate of competitors, b is its own rate sensitivity and $d(m)$ is the cross-bank substitutability of deposits. Search operates through $d(m)$: as more depositors compare offers, deposits become more substitutable across banks, making each bank's deposit supply more sensitive to competitors' rates. Banks set deposit rates to maximize their return $(R - r_i)D_i$.

The sequence of events in the model is summarized below.

$t = 0$	$t = 1$	$t = 2$
• Deposit rate shock Δr_A in local market A creates a social-media buzz of intensity μ_A • Depositors in local market B become aware with $p(w_{BA}, \Delta r_A)$	• Aware depositors in B choose whether to search • Share of searchers: m	• Banks set deposit rates r_B^*

The key mechanism operates through households' search choice. The payoff from search depends on how many other depositors also search. When more depositors become active, local banks face depositors who are more sensitive to competitors' rates, and respond by raising deposit rates. Higher rates, in turn, make search more attractive to aware households. Search decisions are therefore strategic complements.

Accordingly, the share of active searchers m is determined as a fixed point. Zero search $m^* = 0$ is always an equilibrium: if depositors expect no one else to search, deposit rates remain at the baseline inattentive level and search is not privately worthwhile. But if awareness is sufficiently high and search costs are low enough, a positive-search equilibrium $m^* > 0$ may also arise, because expectations of search by others induce banks to raise rates enough to validate those expectations. Social-media buzz therefore raises

awareness without uniquely pinning down search behavior. Conditional on selection of the positive-search equilibrium, the endogenous share of active searchers $m^* > 0$ increases in both strength of social connections w_{BA} and financial sophistication λ.[3]

Then the symmetric equilibrium deposit rate in county B is

$$r_B^*(w_{BA}, \lambda) = \frac{bR - a}{2b - d\big(m^*(w_{BA}, \lambda)\big)}.$$

Deposit rates in county B respond to shocks in A due to the rise in social-media-driven awareness and the resulting increase in depositor's search activity. A larger share of active searchers raises the substitutability of deposits across banks, making each bank's deposit supply more sensitive to competitors' rates, intensifying local competition and raising equilibrium deposit rates.

This mechanism yields two empirical predictions. First, social networks counties more connected to A are more likely to experience larger spillovers. Second, local markets with more financially sophisticated households might exhibit a stronger response because awareness triggers more search activity. This enables us to formulate two hypotheses.

Hypothesis 1: *Local markets that are more socially connected to a market experiencing a deposit rate shock are more likely to exhibit larger increases in local deposit rates.* Intuitively, social connections increase exposure to deposit-related content, raising awareness and prompting more depositors to search.

Hypothesis 2: *The social spillover effect is stronger in local markets with more financially sophisticated households.* Intuitively, lower search costs mean that awareness translates more readily into search behavior, raising the substitutability of deposits across banks and strengthening the rate response.

The model, therefore, links the size of the spillover to three observable inputs: (i) the magnitude of the shock in local market A, (ii) the intensity of social connections between

[3] Eichenbaum et al. (2025) also allow social interaction to shape depositor attention, but without the coordination problem just described. In their model, random meetings move households between attentive and inattentive states at a rate that rises with the aggregate policy rate, so attention—and hence deposit-rate pass-through—varies over the interest-rate cycle within a single market. Their mechanism thus governs the level of aggregate attention over time. Ours instead makes a localized shock salient across specific markets and turns search decisions into a strategic complements, and with it introducing the possibility of multiple equilibria in the cross-market transmission of that shock.

county A and B, and (iii) the financial sophistication level of depositors in B. We proceed by mapping these inputs into the data.

3 Data and social connectedness

Next, we describe the data used to test the model's predictions. We merge bank, economic and other demographic data from several sources at the county level, our definition of a local market.

3.1 Branch-level bank data

We draw deposit rate data from the RateWatch branch-level deposit rates database. RateWatch surveys over 100,000 bank branches weekly to collect advertised deposit rates and annual percentage yields (APYs) on new accounts. Our sample comprises all branches of commercial banks and savings & loans institutions with valid Federal Deposit Insurance Corporation (FDIC) identifiers that report to RateWatch over the period 2011 to 2023.[4] We focus on the brick and mortar branches only, excluding deposits and rates of online banks listed in Erel, Liebersohn, Yannelis & Earnest (2023). Online banks operate beyond any local market, so it would be impossible to attribute deposits of online banks to any geographically specific or socially connected area.

We retain both "rate-setter" and "follower" branches, since excluding followers—whose rates are centrally determined—would eliminate over 90% of US commercial bank branches (Begenau & Stafford 2023). Including follower branches, many of which belong to large banks, also reflects the empirical distinction between large banks' more uniform pricing and small banks' greater responsiveness to local competitive conditions.

RateWatch tracks a wide array of standardized deposit products such as checking accounts, savings products, and certificates of deposits (CDs) of different sizes and maturities. We focus on one of the most common products: the 12-month CD with a $10,000 minimum account size (*12m10K*). To test the robustness of our findings across different maturities and sizes, we also report results from two additional deposit products: the 6-

[4] Our rate data for year 2023 ends in the third quarter.

month CD with a $10,000 minimum account size (*6m10K*) and the 12-month CD with a $100,000 minimum account size (*12m100K*). We construct a quarterly dataset by keeping the rate quotes from the last month of a given quarter.

RateWatch also includes the FDIC branch identifier and the identity of the financial institution that owns each branch. We use these identifiers to merge the RateWatch data with the Summary of Deposits (SoD) dataset, an annual survey conducted as of June 30, that collects information on deposits held in branch offices of all FDIC-insured institutions, including insured US branches of foreign banks.[5] This dataset provides a comprehensive listing of branch office locations and the total deposits reported by each branch. Using the asset data reported in the SoD, we classify banks as "large" if their total amount of assets (averaged over the period) exceeds $100 billion, following the FED's definition of large banking organizations.[6] We use this data to compute the Herfindahl-Hirschman index for small banks within a county-level deposit market, denoted as (*SB-HHI*), and the deposit market share of large banks, denoted as (*LBMS*). These variables serve as proxies for local competition and market power of large institutions. In addition, we include information from the FDIC on branch closures and from the Federal Financial Institutions Examination Council (FFIEC) on bank merger activity.

3.2 County-level social connectedness

To measure the intensity of social connectedness between counties, we rely on the Social Connection Index (SCI), first introduced by Bailey, Cao, Kuchler & Stroebel (2018) and provided by Facebook. Social connectedness between two locations i and j is the number of Facebook (FB) friendship links between the two counties, normalized by the product of the two counties' Facebook (FB) users:[7]

[5] To align the quarterly deposit rate data with the annually updated SoD, published each June, we pair the SoD with the Rate data as follows: deposit rates of quarters 1 and 2 with SoD data published in the year t and deposit rates of quarters 3 and 4 with SoD data published in the year $t+1$.

[6] Federal Reserve: Large Banking Organization Supervision.

[7] The version of the SCI data available to us is equal to the social connectedness value divided by the maximum value in the dataset, and then multiplied by one billion. For further details on the methodology for the construction of the index, see Facebook's documentation at `https://dataforgood.facebook.com/dfg/tools/social-connectedness-index`.

$$Social\ connectedness_{i,j} = \frac{number\ of\ FB\ friendship\ links_{i,j}}{FB\ Users_i \times FB\ Users_j} \tag{1}$$

The SCI is constructed from a snapshot of Facebook connections taken in August 2020. Given that Facebook is mostly used to connect with friends and family in real life, the SCI reflects persistent patterns of social interaction that are largely stable over time (Flynn & Wang 2025).

A growing literature shows that the SCI captures economically meaningful peer effects in financial decisions.[8] In particular, Hu (2022) shows that flooding events and insurance campaigns affecting socially connected but geographically distant households increase local insurance demand. Because these shocks do not alter local fundamentals, they isolate responses transmitted through social networks and mitigate standard peer-effects identification concerns. This evidence supports our use of deposit-market shocks in connected counties and, by showing that SCI mainly operates through attention and salience rather than technical information, closely matches our mechanism.

3.3 County-level characteristics

We define the bank's local market as the counties in which the bank has physical branches. Our sample includes all counties across US states with complete data over the period 2011 to 2023, excluding Alaska and Connecticut.[9] County-level population data are sourced from the Surveillance, Epidemiology, and End Results (SEER) Program.[10] We control for the total population of each county (*Population*). Moreover, demographic variation in savings behavior affects local deposit markets (Becker 2007) including deposit prices (Avramidis & Pennacchi 2025), so we include the proportion of the population above 65 years old (*Seniors*) as a control. We also control for deposit supply using

[8] Applications include housing and mortgage choices (Bailey, Cao, Kuchler & Stroebel 2018, Bailey et al. 2019), investor portfolio and trading behaviour (Bali, Hirshleifer, Peng, Tang & Wang 2021, Kuchler et al. 2022), online credit supply and demand (Allen, Peng & Shan 2020), insurance demand (Hu 2022), trade (Bailey, Gupta, Hillenbrand, Kuchler, Richmond & Stroebel 2021), product adoption (Bailey et al. 2022), and bank lending (Rehbein & Rother 2025).

[9] Over our sample period, Alaska experienced frequent redraws of local "boroughs" - the geographical equivalent to a county - making it difficult to construct time-consistent local characteristics. Similarly, in 2022, the US Census Bureau adopted nine new planning regions as county-equivalents replacing Connecticut's eight counties used historically.

[10] The data can be downloaded from `https://seer.cancer.gov/popdata`.

the county-level total deposits per capita (measured in thousands) (*Depositpc*) sourced from the FDIC's summary of deposits database. To capture local economic activity, we use county-level GDP adjusted for inflation and divided by total population (*Realgdppc*) sourced from the Bureau of Economic Analysis.

We also account for customers' financial sophistication, a local demographic factor shown to interact with banks' deposit market power (Drechsler et al. 2017). Following the literature, we measure financial sophistication (*FSophistication*) combining two population characteristics: educational attainment and stock market participation. Educational data are drawn from the Census Bureau data and the American Community Survey. County-level education data reflect the proportion of the population aged 25 years or older across seven categories: "Less than 9th grade", "9th to 12th grade", "no diploma High school graduate (includes equivalency)", "Some college, no degree", "Associate's degree", "Bachelor's degree" and "Graduate or professional degree". To measure stock market participation, we use county-level data from the IRS Statistics of Income (SOI) on Individual Income Tax Returns, specifically the share of tax returns reporting dividend income and capital gains.

To construct a county-level measure of financial sophistication, we apply Principal Component Analysis (PCA) to the set of nine correlated county-level variables: the seven educational attainment categories and the two indicators of stock market participation. This method yields a data-driven, parsimonious measure that captures the largest shared variance across these dimensions. By constructing an orthogonal index that efficiently summarizes the latent construct of financial sophistication, PCA mitigates noise and idiosyncratic variation, as well as concerns about multicollinearity and interpretational complexity, that would arise from including all nine variables separately. The first principal component explains over 50% of the common variance, exhibiting loadings that are consistent with the interpretation of this variable as a county-level financial sophistication measure. Specifically, it assigns negative loadings to the three lowest education categories and positive loadings to the remaining levels. Further information on the derivation of the financial sophistication index using PCA is provided in Appendix E.

4 Social connectedness and deposit rates

4.1 Social proximity measures

To examine social spillovers in deposit pricing, we construct a measure of the social proximity between households in a focal county c and deposit rates offered by banks in socially connected counties j. To remove spillover effects from adjacent counties, we exclude all counties that are within a 25-mile radius from the focal county c.

Our primary explanatory variable is *Social Deposit Rate* (SDR), which captures county c's indirect exposure to deposit rate changes at time t through social connections with all other counties. This variable is defined as:

$$SDR_{c,t} = \frac{1}{s(c)} \sum_{j \in \mathcal{J}_c^{25}} SCI^*_{c,j} \times \Delta r_{j,t} \tag{2}$$

where $SCI^*_{c,j}$ is the SCI between counties c and j, standardized for interpretation reasons by the total number of connections (in 10,000) within our sample's counties, $\Delta r_{j,t}$ is the change in deposit rates in county j at time t, and $\mathcal{J}_c^{25}$ denotes the set of all counties that are at least 25 miles far from the focal county c. Since deposit-rate changes may not be observed for every peer county in every year, we rescale the weighted sum by the fraction $s(c)$ of total SCI weight of peers with available rate data.[11]

The *Social Deposit Rate* variable assigns greater weight to counties that are more socially connected to county c. A high $SCI^*_{c,j}$ implies that deposit rate information is more likely to diffuse from county j to county c, potentially influencing local bank pricing decisions even in the absence of direct market interactions.

Similarly, to instrument for this exposure, we introduce a second variable, *Social Large Bank Branch Closure* ($SLBC$) defined as:

$$SLBC_{c,t} = \sum_{j \in \mathcal{J}_c^{25}} SCI^*_{c,j} \times LBC_{j,t} \tag{3}$$

where $LBC_{j,t}$ is an indicator variable capturing large bank branch closures in county j

[11] This adjustment prevents missing peer outcomes from being implicitly treated as zero and makes the exposure measure comparable across county-year observations with different data coverage.

at time t.[12]

The underlying premise is that such closures may instrument the deposit behaviour and pricing strategies in socially connected counties. Therefore, our identification strategy relies on the assumption that branch closures are not confounded with other local characteristics. To ensure this condition, we focus on branch closures of large banks that have been involved in a merger within a window of two years. Such branch closures are more likely to be associated with decisions unrelated to local trends, including cost-cutting overheads of overlapping branches and broader restructuring of the branch network (Garmaise & Moskowitz 2006). Appendix C presents the branch-closure data used in the analysis and the construction of our county-level closure measure. The evidence suggests that large bank branch closures display sufficient geographic and temporal coverage, allowing us to identify plausibly exogenous local disruptions associated with bank consolidation.

More broadly, social connectedness tends to be positively correlated with geographic proximity, as well as with economic and cultural factors (Bailey, Cao, Kuchler, Stroebel & Wong 2018). In our empirical specification, therefore, we include two alternative exposure measures analogous to (2), but with weights based on geographic and economic proximity. Specifically, the *Distant Deposit Rate* (DDR) is defined as:

$$DDR_{c,t} = \frac{1}{d(c)} \sum_{j \in C-c} Dist_{c,j} \times \Delta r_{j,t}$$

where $Dist_{c,j}$ is the inverse physical distance between counties c and j using the NBER County Distance Database and the Haversine formula based on internal points in the geographic area and $d(c)$ is the rate data availability adjustment factor for the distance measure. This formulation assigns greater weight to counties that are geographically closer to county c, allowing us to disentangle the influence of spatial proximity from that of social connectedness.

Economic proximity – economic linkages between counties due to similarities in in-

[12] Because the closure measure is observed for all peer county-years, no missing-data adjustment is required for $SLBC_{c,t}$.

dustry composition – could also explain our findings. Counties with similar industrial structures may exhibit stronger social ties through trade, labor mobility, or migration patterns. Following Flynn & Wang (2025), we construct economic linkages based on industry composition. Using employment data by industry from the Bureau of Labor Statistics' (BLS) Quarterly Census of Employment and Wages, we calculate the share of total county employment in each 2-digit NAICS sector. For each county-year, we compute the cosine similarity of industry employment shares, denoted as $EP_{c,j,t}$. To capture the indirect exposure of county c to deposit rate changes in economically connected counties, we construct the *Economic Proximity Deposit Rate* ($EPDR$) variable as follows:

$$EPDR_{c,t} = \frac{1}{e(c)} \sum_{j \in C-c} EP_{c,j,t} \times \Delta r_{j,t}$$

where $EP_{c,j,t}$ is the industry cosine similarity (divided by 1,000) between county c and j and $e(c)$ is the rate data availability adjustment factor for the economic-proximity measure.

4.2 Empirical specification

Our identification strategy hinges on the exogeneity of the variable *Social Deposit Rate*, defined in (2), which captures the extent to which county c is exposed through social ties to rate changes that occur in other counties. While deposit rate changes may be driven by broad macroeconomic or monetary factors simultaneously affecting several counties, our aim is to isolate deposit rate changes that originate from local market disruptions, such as large bank exits, and propagate across socially connected counties. To ensure that the variation in *Social Deposit Rate* (SDR) is truly exogenous, we instrument it using *Social Large Bank Branch Closure* ($SLBC$), constructed in (3). This *shift-share* (Bartik-type) instrument combines closures of large bank branches in socially connected areas (*shift*) and SCI values (*shares*) that quantify the strength of ties between counties.

We contend that the *shift* component is exogenous to the focal county's deposit market. Most socially connected counties are geographically and administratively distinct,

especially after imposing the 25-miles exclusion criteria, making unlikely that merger-induced branch closures of large banks in peer counties are influenced by market conditions in the focal county. We also argue that the *share* component is not confounded with deposit rate changes in either the focal county or the connected counties. As noted by Borusyak, Hull & Jaravel (2022) the validity of the *shift-share* instrument can be maintained even without assuming exogeneity of the shares, provided that shifts are numerous and exogenous. Thus, our instrument remains valid even under relaxed assumptions regarding the social connection weights. In a separate section below, we present evidence supporting the instrument's relevance and robustness exercises that are consistent with the exclusion restriction. Furthermore, branch closure data in the Appendix C show the sufficient coverage both geographical and over time.

Based on the above, we test whether deposit rates in a focal county c are affected by rate changes in socially connected counties, using a two-stage least squares (2SLS) regression setup. First, we estimate the following regression:

$$SDR_{c,t} = \beta + \beta_1 SLBC_{c,t} + \beta_2 \Delta x_{c,t} + f_c + f_t + \epsilon_{c,t} \tag{4}$$

and use the estimated $\widehat{SDR}_{c,t}$ in the following second-stage regression:

$$\Delta r_{c,t} = \gamma + \gamma_1 \widehat{SDR}_{c,t} + \gamma_2 \Delta x_{c,t} + f_c + f_t + \epsilon_{c,t}. \tag{5}$$

The key parameter of interest is γ_1 capturing the social spillover effect on deposit rate changes. We control for geographic proximity between counties using the *Distant Deposit Rate* (DDR) measure and for economic proximity using the *Economic Proximity Deposit Rate* ($EPDR$) measure. Moreover, we control for the change in the large bank market share ($\Delta LBMS$) and in small banks' market concentration HHI ($SBHHI$), so that socially transmitted shocks from other counties are clearly separated from any local competitive effects.[13] Other control variables include changes in demographic factors known for their

[13] Local markets experiencing small or large bank branch closures simultaneously with their socially connected counties are omitted from the sample. The inclusion of large bank market share together with the small bank concentration measure aim to capture any local competitive effects unrelated to branch changes.

influence on deposits: the percentage of senior population (*Seniors*), total population (*Population*), supply of deposits per capita (*Depositpc*), real GDP per capita (*Realgdppc*) and financial sophistication level (*FSophistication*) in the county. Finally, we include county fixed effects, f_c, to ensure that estimates are not driven by cross-sectional county differences, as well as time fixed effects, f_t, to exclude cross-year variations. The error term, $\epsilon_{c,t}$, is adjusted for within-county correlation and for the variability introduced by the first-stage estimation.

To test for our second research hypothesis, we augment the baseline specification with an interaction between $SDR_{c,t}$ and $HighFSoph_c$, an indicator equal to one when a county's time-averaged financial-sophistication index exceeds the cross-county median, and zero otherwise. We instrument the endogenous interaction with $SLBC_{c,t} \times HighFSoph_c$.

4.3 Panel regression estimates

We estimate the model equation (5) and its extension using data over the period 2015 to 2023.[14] We select this sample period because Facebook penetration across US counties exceeded 70% of total US population.[15] This threshold ensures that social connections captured by the SCI are representative of broader population-level interactions and relevant for the impact of social spillovers on local banking decisions. Moreover, the model is estimated after winsorizing all variables at the 1st and 99th percentiles.

Tables B1, B2 and B3 in Appendix B report summary statistics for the deposit rates, the socially connected rates and the main control variables in the form (time-differences) used in the empirical analysis. Table B4 in Appendix B gives the definition of the variables.

Columns (1)-(3) in Table 1 show the second-stage estimates from equation (5). In all specifications, we find a strong, positive and statistically significant relationship suggesting that small banks in a focal county increase their deposit rates when small banks

[14] Because the model uses time differences of variables, the effective period starts from 2016. Moreover, differences for year 2023 are calculated based on the third quarter.

[15] Facebook was launched in 2004 and despite its growth, only 50% of US adults were using it by 2011. According to Statista, Facebook's penetration rate in the North America population surpassed 70% in 2016 (https://www.statista.com/statistics/247614/number-of-monthly-active-facebook-users-worldwide/). This year coincides with the acceleration of Facebook's mobile-platform which increased user engagement throughout the day.

in socially connected counties raise theirs in response to local competition changes. For *12m10K*, the coefficient of 0.111 implies that a one standard deviation increase in the SCI-weighted deposit-rate exposure raises the focal county's deposit rate by approximately 19 basis points.

Moreover, the effects of geographic proximity *DDR* and economic proximity *EPDR* are positive and significant, confirming that proximate or economically-linked counties exert competitive pressures. This suggests that our measure of social proximity of deposit rates captures social spillover effects that are distinct from physical or economic proximity between counties. Finally, higher GDP per capita change is associated with higher deposit rate changes offered by small banks.

Next, we test whether the social spillover effect is more pronounced in markets with more financially sophisticated households. Columns (4)-(6) of Table 1 show that small banks' deposit rates respond more strongly to exogenous rate changes in socially connected counties if the focal market has a large base of financially sophisticated depositors. This supports the argument, as in Drechsler et al. (2017) and others, that banks have greater market power over financially unsophisticated customers, enabling them to offer lower deposit rates with low risk of outflows. Therefore, financial sophistication amplifies the effect of online social networks on deposit pricing.

Given that higher financial sophistication is typically associated with more active online social engagement (Gambacorta et al. 2023), this dynamic intensifies the transmission of deposit rate information across socially connected areas. Importantly, the differential effect observed between high and low sophistication counties suggests that the spillover is less likely to be driven by social connections between bankers themselves. If banker-to-banker ties were the primary channel through which social ties affect deposit rates, we would expect a uniform response across counties regardless of customer sophistication. Instead, the stronger pass-through in high sophistication counties indicates a customer-driven social network as the conduit for rate information.

4.4 Validation test of instrument

A growing literature shows that banks tend to set deposit rates uniformly across markets (Begenau & Stafford 2023) and that large and small banks compete on different margins, with large banks paying lower deposit rates on average and serve less rate sensitive customers, whereas small banks rely more on price competition and offer higher rates to attract depositors (d'Avernas et al. 2023).[16] Crucially, small bank pricing depends on the local competitive environment. d'Avernas et al. (2023) show that small banks facing greater large bank presence offer lower deposit rates than those in markets where large banks are less prevalent. It follows that the exit of a large bank should lead small banks to raise their rates, which is the margin our instrument exploits.

This dynamic is illustrated by PNC Bank's acquisition of BBVA USA. Following the merger, PNC closed branches in Birmingham, Alabama, providing a natural experiment: nearby small-bank branches raised deposit rates by more than branches further away, consistent with a competitive response to the large bank's exit. Appendix F presents this case study in full.

To test formally the relevance of our instrument, we regress the merger-driven large bank branch closure indicator $LBC_{j,t}$ on changes in rates of deposits of different sizes and maturities, $\Delta r_{j,t}$:

$$\Delta r_{j,t} = \beta + \beta_1 LBC_{j,t} + \beta_2 \Delta x_{j,t} + f_j + f_t + \epsilon_{j,t}. \tag{6}$$

The results in columns (1)-(3) in Table 2 support the validity of the instrument. Specifically, the results confirm that large bank closures raise small bank deposit rates. Moreover, when we run the model on large bank rates, columns (4)-(6) in Table 2 show that large bank rates do not respond to local concentration changes, consistent with their uniform pricing across regions.

[16] d'Avernas et al. (2023) attribute the lower rate sensitivity of large bank customers to their willingness to pay for the superior liquidity services – extensive branch and ATM networks, more sophisticated online banking, and a broader range of financial products – which allows large banks to sustain lower rates across markets.

4.5 Robustness tests

Next, we present several robustness tests and try to eliminate other potential mechanisms. First, we examine whether social spillovers still hold if we concentrate on a county's strongest social connections. *Social Deposit Rate* assigns positive weight to all socially connected counties, including those links that may be too weak to facilitate meaningful information transmission. Aggregating rate changes across such a broad and diffuse network could cause the measure to capture common macroeconomic movements affecting deposit rates rather than information transmitted through social ties. Another concern is that after aggregating over all counties, variation could come from counties that are rather unimportant in size. We therefore restrict the network to each county's strongest connections and test whether the estimated spillovers persist among the ties most likely to support meaningful information diffusion.

We recalculate *Social Deposit Rate* using only the focal county's strongest social ties. Specifically, after excluding all counties within 25 miles, we compute the county-specific 90th percentile $p_{90,c}$ of $SCI^*_{c,j}$ and retain links with an SCI weight equal or above this threshold. Since multiple links may share this threshold, this procedure retains approximately the strongest 10 percent of social ties. The retained set is defined as

$$\mathcal{T}_c = \left\{ \mathcal{J}_c^{25} \ \cap \ SCI^*_{c,j} \geq p_{90,c} \right\}. \tag{7}$$

Using these retained links, the *Top-Ties Social Deposit Rate* is defined as

$$SDR^{Top}_{c,t} = \frac{1}{s(c)} \sum_{j \in \mathcal{T}_c} SCI^*_{c,j} \times \Delta r_{j,t}. \tag{8}$$

We adjust again for missing peer-county rate observations according to the share $s(c)$ of retained SCI weight represented by peers with available data. This prevents missing rate changes from being implicitly treated as zeros. We apply the same sparse SCI matrix to merger-related large-bank closure events in peer counties to *Top-Ties Social Large-bank Branch Closure*:

$$SLBC_{c,t}^{Top} = \sum_{j \in \mathcal{T}_c} SCI_{c,j}^{*} \times LBC_{j,t}, \tag{9}$$

where $LBC_{j,t}$ denotes the merger-related large bank closure indicator. Table 3 replicates the baseline specifications using $SDR_{c,t}^{Top}$ and $SLBC_{c,t}^{Top}$.[17] The results show that the estimated effect of social spillovers is not driven by the large number of weak links in the full social network. Instead, they remain significant when social exposure is restricted to the strongest geographically non-local ties.

Second, we construct a constrained randomized-network placebo measure. For each focal county c, we transfer the SCI weights attached to its strongest social ties to a set of weaker, non-top social connections. The placebo peers are selected from counties that remain socially connected to county c after the 25-mile exclusion but do not belong to its top-ties network $\mathcal{T}_c$. To ensure that the placebo does not simply replace the original peers with fundamentally different counties, we select replacement peers that are as similar as possible in geographic distance, Census division, and economic proximity. Each placebo peer is used at most once within a focal county.

The resulting network preserves, for each focal county, the number of county-pair connections, the SCI weights assigned to those county-pairs and the sparsity of the strongest-ties network, while changing the identities of the counties receiving the weights. Specifically, let $\mathcal{P}_c$ denote the set of placebo peers assigned to focal county c, and let $SCI_{c,j}^{P}$ denote the SCI weight transferred to placebo peer j. The placebo social deposit-rate exposure is defined as

$$SDR_{c,t}^{P} = \frac{1}{s(c)} \sum_{j \in \mathcal{P}_c} SCI_{c,j}^{P} \times \Delta r_{j,t}. \tag{10}$$

As before, missing peer-county observations are handled using the available-weight adjustment $s(c)$. We construct the corresponding placebo social large-bank branch closure as:[18]

[17] Both *Top-Ties Social Deposit Rate* and *Top-Ties Social Large-bank Branch Closure* are winsorized at the 1st and 99th percentiles.

[18] Applying the same placebo matrix to both the endogenous exposure and the instrument ensures that the specification is internally consistent.

$$SLBC^{P}_{c,t} = \sum_{j \in \mathcal{P}_c} SCI^{P}_{c,j} \times LBC_{j,t}. \tag{11}$$

Table 4 re-estimates the baseline specifications using the placebo exposure measures and their corresponding instruments. Reassigning the weights of the strongest social ties to weaker but geographically and economically comparable connections renders the estimated effects insignificant. This is consistent with the baseline results depending on the identities of the counties connected by the strongest ties, rather than on the weighting structure or common rate-relevant geographic and economic forces.[19]

Third, we run a set of additional robustness tests presented in Appendix D. Large bank mergers may have indirect effects in focal areas. To address this concern, we restrict our sample to counties where there is no large bank presence. Table D1 confirms the findings presented in the baseline specifications. Moreover, we replace time fixed effects with census division-time fixed effects to capture any regional time-varying trends.[20] Table D2 shows that the main effect turns out statistically insignificant while the interaction effect remains positive and statistically significant. Arguably the inclusion of regional-time varying effects weakens the identification which relies on county-specific time varying changes in social connected exposure to deposit rate changes. Finally, we apply a more restrictive condition for geographical proximity by excluding from the social spillover measures (2)-(3) the counties within a 50-mile radius from the focal county c. This ensures that the remaining socially connected counties are even more distant, thereby isolating the role of social networks. Table D3 shows that the results remain broadly consistent with our main findings, although the interaction effects are statistically weaker. Finally, we present the first-stage results for the main analysis. Table D4 shows that exposure to merger-related large-bank closures positively predict the social deposit-rate measures in both the full and sparse networks.[21]

[19] The placebo instruments are weak, so the insignificant estimates indicate an absence of evidence for an effect, rather than evidence of no effect.

[20] The US Census Bureau divides the country into nine Census divisions: New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific.

[21] A one-standard-deviation increase in $SLBC$ of 0.071, as reported in Table B2, is associated with an increase of approximately 0.172–0.198 in SDR. Similarly, a one-standard-deviation increase in $SLBC^{Top}$

5 Social connections and uniform pricing

The previous section offers empirical evidence that social connections transmit financial information and influence small banks' deposit price decisions. Building on this, we now examine empirically a corollary: as social network engagement among customers of banks intensifies, deposit rates across all socially connected counties become more homogeneous. This stems from faster information diffusion across banks and counties, which reduces local pricing heterogeneity and promotes convergence toward a common deposit rate.

To test this corollary, we assess whether stronger social linkages are associated with greater uniformity in small bank deposit rates across socially connected areas. Specifically, we employ a β-convergence framework, commonly used to evaluate whether regions with initially lower levels of a variable, such as GDP per capita, grow faster than those with higher levels and eventually converging over time (Barro & Sala-i Martin 1992, Kremer, Willis & You 2022).

The simplest β-convergence model is:

$$\Delta Y_{i,t} = \alpha + \beta Y_{i,t-1} + \epsilon_{i,t} \tag{12}$$

where Y is the variable of interest. A negative and statistically significant β indicates convergence, as lower lagged values of Y are associated with higher growth rate.

In our context, the variable of interest is $Y_{i,t} = r_{c,t} - r^{sc}_{c,t}$, that is the gap between the deposit rates $r_{c,t}$ of small banks in county c and the weighted average deposit rate of its socially connected peers, $r^{sc}_{c,t}$ which is measured from:

$$r^{sc}_{c,t} = \sum_{j \in \mathcal{J}^{25}_c} \frac{SCI_{c,j}}{\sum_{k \in \mathcal{J}^{25}_c} SCI_{c,k}} r_{j,t},$$

Thus, the outcome variable $\Delta Y_{i,t}$ becomes $\Delta(r_{c,t} - r^{sc}_{c,t}) = (r_{c,t} - r^{sc}_{c,t}) - (r_{c,t-1} - r^{sc}_{c,t-1})$. Our current objective is to test whether the increasing use of social networks over time accelerates the convergence of deposit rate changes of small banks. To capture time-

of 0.068 is associated with an increase of approximately 0.156–0.180 in SDR^{Top}.

variation in the intensity of social network usage, we define:

$$SC_{c,t-1} = \sum_{j \in \mathcal{C}_c^{25}} SCI_{c,j} \times U_{t-1}.$$

where U_t is the total number of Facebook users at time t across all North America (scaled by one billion).[22] Our new sample period is 2011-2023, during which Facebook's total monthly active users in the US (and Canada) increased from 163 million to 271 million, a 66% increase.[23] This substantial growth in user engagement provides meaningful variation in U_t enabling us to capture the evolving influence of social networks on deposit rate convergence. We incorporate this measure into a modified β-convergence framework by interacting it with the lagged deposit rate gap between county c and its social peers. Specifically, using quarterly data from 2011q2 to 2023q3, we estimate the following panel regression model:

$$\begin{aligned}\Delta(r_{c,t} - r_{c,t}^{sc}) = \alpha_1 SC_{c,t-1} + \alpha_2 SC_{c,t-1} \times (r_{c,t-1} - r_{c,t-1}^{sc}) + \\ \beta(r_{c,t-1} - r_{c,t-1}^{sc}) + x_{c,t} + f_c + f_t + \epsilon_{c,t}. \end{aligned} \tag{13}$$

where $x_{c,t}$ denotes the county-level control variables used in the previous section but now measured in levels while the population is in logs. This panel specification exploits within-county changes over time while absorbing county fixed effects and common quarterly shocks.

The negative and statistically significant estimate of α_2 in columns (1)-(3) of Table 5 indicates that social connections accelerate convergence in small bank deposit rates. The negative and statistically significant estimate of β suggests that convergence also occurs beyond social spillovers. This plausibly reflects consolidation among small and medium-sized banks, which pushes small banks toward multi-market business models as well as the rise of online banks and internet-based information flows, which pressure local banks toward uniform pricing behaviour. Taken together, our empirical results show that while

[22] The geographic structure of networks between regions is highly stable over time suggesting that social connectedness measured today is likely to predict interactions over multiple time horizons. For example, Bailey et al. (2021) document that the underlying trade-facilitating relationships proxied by SCI are very stable over time.

[23] Facebook monthly active users data is downloaded from Statista https://www.statista.com/statistics/247614/number-of-monthly-active-facebook-users-worldwide/.

multiple forces contribute to deposit rate convergence of small banks, social networks play a key and distinct role in accelerating this process.

Finally, we apply the panel regression model (13) to deposit rates of large banks. As shown in columns (4)-(6) of Table 5, the coefficient α_2 is statistically weaker, indicating some evidence that social connectivity is associated with faster convergence in deposit rates among large banks. However, as expected, the main effect of the deposit rate gap $(r_{c,t-1} - r^{sc}_{c,t-1})$ remains negative and statistically significant, consistent with prior studies predicting that structural factors, such as internet penetration and the expansion of online banking, underpin uniform pricing strategies of large multi-market banks (Park & Pennacchi 2008).

6 Conclusions

We identify social networks as a novel determinant of local deposit rates and banks' pricing power and a distinct channel for transmitting financial information, shaping deposit pricing, particularly among small banks.

The mechanism operates through depositor attention and coordinated search. A deposit rate change in one market becomes salient to inattentive depositors in socially connected counties, inducing search, especially among financially sophisticated households facing lower search costs. Because search is self-reinforcing, greater participation makes deposits more substitutable, weakens small banks' market power, and raises rates. Spillovers therefore increase with bilateral connectedness and the financial sophistication of the receiving market — the two dimensions we exploit empirically.

First, using exogenous shifts in local market structure across socially connected counties, we confirm these spillovers: small banks rates rise in response to rate changes transmitted through social connections, beyond what geographic and economic proximity explain. A placebo test that assigns the same SCI weights to counties with weak social connections yields no evidence that our findings are driven by unobserved regional trends. Likewise, an analysis based on each county's actual strongest social ties confirms our main findings.

Second, we show the spillover is stronger where depositors are more financially sophisticated, using a proxy that combines educational attainment and stock market participation. We find that banks serving more sophisticated customers have lower pricing power, as these depositors are more ready to act on rate information reaching them through social networks and to search for better returns on their deposits.

Finally, we explore the long-run implication of these findings for the convergence toward a common rate among small banks in socially connected counties. We find that the deposit rate gap between small banks and their social peers narrows faster the more socially connected a county becomes.

Our findings highlight social networks as a complementary and increasingly powerful dimension of deposit market dynamics. As small banks respond more to socially transmitted competitive pressures, the transmission of monetary policy through the deposit rate channel may have uneven effects across bank types — an informational channel that models of rate pass-through should account for. Deposit rate changes, whether driven by policy changes or competition, might have implications for geographically distant but socially connected markets, amplifying the reach of monetary interventions. The convergence of deposit rates across markets, accelerated by digital technologies, suggests that geographic barriers to monetary policy transmission are diminishing.

References

Adams, P., Hunt, S., Palmer, C. & Zaliauskas, R. (2021), 'Testing the effectiveness of consumer financial disclosure: Experimental evidence from savings accounts', *Journal of Financial Economics* **141**(1), 122–147.

Ahnert, T. & Bertsch, C. (2022), 'A wake-up call theory of contagion', *Review of Finance* **26**(4), 829–854.

Allen, L., Peng, L. & Shan, Y. (2020), 'Social connectedness and peer influences: Impact on online credit supply and demand', *Available at SSRN 3537714* .

Avramidis, P. & Pennacchi, G. G. (2025), 'The effects of an aging population on the structure of bank assets and liabilities', *Journal of Money, Credit and Banking* **57**(8), 2211–2251.

Bailey, M., Cao, R., Kuchler, T. & Stroebel, J. (2018), 'The economic effects of social networks: Evidence from the housing market', *Journal of Political Economy* **126**(6), 2224–2276.

Bailey, M., Cao, R., Kuchler, T., Stroebel, J. & Wong, A. (2018), 'Social connectedness: Measurement, determinants, and effects', *Journal of Economic Perspectives* **32**(3), 259–280.

Bailey, M., Dávila, E., Kuchler, T. & Stroebel, J. (2019), 'House price beliefs and mortgage leverage choice', *The Review of Economic Studies* **86**(6), 2403–2452.

Bailey, M., Gupta, A., Hillenbrand, S., Kuchler, T., Richmond, R. & Stroebel, J. (2021), 'International trade and social connectedness', *Journal of International Economics* **129**, 103418.

Bailey, M., Johnston, D., Kuchler, T., Stroebel, J. & Wong, A. (2022), 'Peer effects in product adoption', *American Economic Journal: Applied Economics* **14**(3), 488–526.

Bali, T. G., Hirshleifer, D., Peng, L., Tang, Y. & Wang, Q. (2021), Social interactions and lottery stock mania, Working Paper 29543, National Bureau of Economic Research.

Barro, R. J. & Sala-i Martin, X. (1992), 'Convergence', *Journal of political Economy* **100**(2), 223–251.

Becker, B. (2007), 'Geographical segmentation of us capital markets', *Journal of Financial economics* **85**(1), 151–178.

Begenau, J. & Stafford, E. (2023), 'Uniform rate setting and the deposit channel', *Available at SSRN 4136858* .

Borusyak, K., Hull, P. & Jaravel, X. (2022), 'Quasi-experimental shift-share research designs', *The Review of economic studies* **89**(1), 181–213.

Calem, P. S. & Nakamura, L. I. (1998), 'Branch banking and the geography of bank pricing', *Review of Economics and Statistics* **80**(4), 600–610.

Cookson, J. A., Mullins, W. & Niessner, M. (2024), Social media and finance, Oxford Research Encyclopedia of Economics and Finance.

d'Avernas, A., Eisfeldt, A. L., Huang, C., Stanton, R. & Wallace, N. (2023), The deposit business at large vs. small banks, Technical report, National Bureau of Economic Research.

Drechsler, I., Savov, A. & Schnabl, P. (2017), 'The deposits channel of monetary policy', *The Quarterly Journal of Economics* **132**(4), 1819–1876.

Egan, M. L., Hortaçsu, A., Kaplan, N. A., Sunderam, A. & Yao, V. (2025), Dynamic competition for sleepy deposits, Working Paper 34267, National Bureau of Economic Research.

Eichenbaum, M. S., Puglisi, F., Rebelo, S. & Trabandt, M. (2025), Banks and the state-dependent effects of monetary policy, Working Paper 33523, National Bureau of Economic Research.

Erel, I., Liebersohn, J., Yannelis, C. & Earnest, S. (2023), Monetary policy transmission through online banks, Technical report, National Bureau of Economic Research.

Fleckenstein, M. & Longstaff, F. A. (2024), Financial sophistication and bank market power, Technical report, National Bureau of Economic Research.

Flynn, S. & Wang, J. (2025), 'Social connections and bank deposits', *Journal of Banking & Finance* p. 107506.

Gambacorta, L., Gambacorta, R. & Mihet, R. (2023), 'Fintech, investor sophistication,

and financial portfolio choices', *The Review of Corporate Finance Studies* **12**(4), 834–866.

Garmaise, M. J. & Moskowitz, T. J. (2006), 'Bank mergers and crime: The real and social effects of credit market competition', *The Journal of Finance* **61**(2), 495–538.

Granja, J. & Paixao, N. (2023), 'Bank consolidation and uniform pricing', *Available at SSRN 3488035* .

Hirshleifer, D. (2020), 'Presidential address: Social transmission bias in economics and finance', *The Journal of Finance* **75**(4), 1779–1831.

Hong, H., Kubik, J. D. & Stein, J. C. (2004), 'Social interaction and stock-market participation', *The Journal of Finance* **59**(1), 137–163.

Hu, Z. (2022), 'Social interactions and households' flood insurance decisions', *Journal of Financial Economics* **144**(2), 414–432.

Kremer, M., Willis, J. & You, Y. (2022), 'Converging to convergence', *NBER Macroeconomics Annual* **36**(1), 337–412.

Kuchler, T., Li, Y., Peng, L., Stroebel, J. & Zhou, D. (2022), 'Social proximity to capital: Implications for investors and firms', *The Review of Financial Studies* **35**(6), 2743–2789.

Lu, X. & Wu, L. (2026), Banking on inattention, Working Paper 34783, National Bureau of Economic Research.

Park, K. & Pennacchi, G. (2008), 'Harming depositors and helping borrowers: The disparate impact of bank consolidation', *The Review of Financial Studies* **22**(1), 1–40.

Rehbein, O. & Rother, S. (2025), 'Social connectedness in bank lending', *The Review of Financial Studies* **38**(9), 2759–2809.

Reis, R. (2006), 'Inattentive consumers', *Journal of Monetary Economics* **53**(8), 1761–1800.

Shiller, R. (2019), *Narrative Economics*, Princeton University Press.

Zhou, X. (2025), 'Financial technology and the transmission of monetary policy: The role of social networks', *Journal of Political Economy Macroeconomics* **3**(1), 122–164.

Tables

Table 1. Social connections and small bank deposit rate changes
The table reports coefficient estimates and standard errors (in parentheses) from second stage regressions. The social-connection measures are constructed using only SCI-connected counties located more than 25 miles from the focal county. The dependent variable is the change in (small bank) rates of deposits of different sizes and maturities (6m10K, 12m10k, and 12m100k). Estimation method is 2SLS with county and time fixed effects. The lower part of the table also reports the number of observations and the Kleibergen-Paap under-identification statistic. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) 6m10K	(2) 12m10K	(3) 12m100K	(4) 6m10K	(5) 12m10K	(6) 12m100K
SDR	0.105***	0.111***	0.103***	0.035	0.055**	0.049*
	(0.018)	(0.018)	(0.019)	(0.027)	(0.026)	(0.027)
SDR × High FSoph				0.074***	0.060***	0.057***
				(0.022)	(0.019)	(0.020)
DDR	0.074***	0.051***	0.048***	0.093***	0.066***	0.063***
	(0.009)	(0.008)	(0.008)	(0.011)	(0.009)	(0.010)
EPDR	0.127*	0.150**	0.139**	0.020	0.067	0.058
	(0.067)	(0.063)	(0.064)	(0.078)	(0.071)	(0.073)
LBMS	0.225	0.267	0.272	0.274*	0.324*	0.328*
	(0.152)	(0.186)	(0.188)	(0.156)	(0.192)	(0.194)
SBHHI	0.100	-0.019	-0.059	0.058	-0.073	-0.111
	(0.151)	(0.185)	(0.191)	(0.159)	(0.193)	(0.198)
Deposit_pc	-0.000	0.001	0.000	0.001	0.003	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Seniors	0.024	-1.377	-1.461	-1.213	-2.503*	-2.577*
	(1.204)	(1.400)	(1.435)	(1.314)	(1.500)	(1.541)
Population	0.001	-0.009	-0.007	0.001	-0.009	-0.007
	(0.006)	(0.008)	(0.008)	(0.006)	(0.008)	(0.008)
Realgdppc	0.001*	0.001*	0.002**	0.001**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
FSoph	0.013	0.009	0.007	0.024*	0.021	0.019
	(0.013)	(0.015)	(0.016)	(0.014)	(0.016)	(0.017)
Obs.	17,234	17,263	17,224	17,234	17,263	17,224
Kl.-Paap rk LM	346.3***	306.1***	289.7***	282.0***	267.3***	250.4***

Table 2. Validation of instrument: Small banks vs large banks

The table reports coefficient estimates and standard errors (in parentheses) from regressions of deposit-rate changes on large-bank branch closures and county-level controls. The dependent variable is the change in deposit rates of different sizes and maturities for small banks and large banks. Columns (1)–(3) report results for small-bank deposit rates, while columns (4)–(6) report results for large-bank deposit rates. The lower part of the table also reports the number of observations and R-squared. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) 6m10K	(2) 12m10K	(3) 12m100K	(4) 6m10K	(5) 12m10K	(6) 12m100K
LBC	0.029***	0.031***	0.033***	0.018***	0.005	-0.003
	(0.010)	(0.012)	(0.012)	(0.005)	(0.007)	(0.008)
SBHHI	0.199	0.217	0.172	0.372***	0.243*	0.140
	(0.137)	(0.168)	(0.172)	(0.115)	(0.128)	(0.161)
Deposit_pc	-0.004***	-0.005***	-0.005***	-0.007***	-0.008***	-0.006***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Seniors	-0.273	-2.190	-2.225	-3.431**	3.754**	3.705*
	(1.226)	(1.399)	(1.442)	(1.392)	(1.723)	(2.030)
Population	0.001	-0.010**	-0.008*	-0.005**	-0.000	0.001
	(0.003)	(0.004)	(0.005)	(0.002)	(0.003)	(0.003)
Realgdppc	0.001*	0.002**	0.002**	0.003***	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
FSoph	0.036***	0.034**	0.032**	0.018	0.034**	0.029*
	(0.013)	(0.015)	(0.016)	(0.013)	(0.014)	(0.017)
Constant	0.172***	0.221***	0.226***	0.071***	0.033***	0.054***
	(0.006)	(0.006)	(0.007)	(0.006)	(0.008)	(0.009)
Obs.	19,715	19,745	19,705	11,219	11,209	11,144
R-squared	0.624	0.666	0.671	0.392	0.403	0.435

Table 3. Strong social connections and small bank deposit rate changes
The table reports coefficient estimates and standard errors (in parentheses) from second stage regressions. The social-connection measures are constructed using only the strongest 10% of SCI-connected counties located more than 25 miles from the focal county. The dependent variable is the change in (small bank) rates of deposits of different sizes and maturities (6m10K, 12m10k, and 12m100k). Estimation method is 2SLS with county and time fixed effects. The lower part of the table also reports the number of observations and the Kleibergen-Paap under-identification statistic. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) 6m10K	(2) 12m10K	(3) 12m100K	(4) 6m10K	(5) 12m10K	(6) 12m100K
Top-Ties SDR	0.109***	0.116***	0.106***	-0.069	-0.049	-0.050
	(0.019)	(0.019)	(0.020)	(0.051)	(0.045)	(0.047)
Top-Ties SDR × High FSoph				0.189***	0.176***	0.165***
				(0.057)	(0.051)	(0.051)
DDR	0.075***	0.052***	0.049***	0.116***	0.090***	0.086***
	(0.009)	(0.008)	(0.008)	(0.015)	(0.013)	(0.014)
EPDR	0.133*	0.154**	0.141**	-0.128	-0.080	-0.083
	(0.069)	(0.064)	(0.065)	(0.106)	(0.092)	(0.094)
LBMS	0.226	0.269	0.273	0.341**	0.426**	0.423**
	(0.152)	(0.186)	(0.188)	(0.169)	(0.210)	(0.212)
SBHHI	0.102	-0.017	-0.055	0.019	-0.142	-0.174
	(0.151)	(0.185)	(0.191)	(0.180)	(0.219)	(0.223)
Deposit_pc	-0.000	0.001	0.000	0.003	0.005	0.004
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Seniors	-0.031	-1.416	-1.510	-2.860*	-4.374**	-4.391**
	(1.207)	(1.403)	(1.437)	(1.688)	(1.878)	(1.915)
Population	0.002	-0.009	-0.007	0.001	-0.009	-0.007
	(0.006)	(0.008)	(0.008)	(0.006)	(0.008)	(0.008)
Realgdppc	0.001*	0.001*	0.002**	0.002***	0.002***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
FSoph	0.012	0.007	0.006	0.039**	0.041**	0.038*
	(0.013)	(0.016)	(0.016)	(0.017)	(0.019)	(0.020)
Obs.	17,234	17,263	17,224	17,234	17,263	17,224
Kl.-Paap rk LM	323.0***	288.1***	271.0***	98.2***	97.8***	102.0***

Table 4. Placebo social connections and small bank deposit rate changes
The table reports coefficient estimates and standard errors (in parentheses) from second stage regressions. The placebo measures reassign the SCI weights of the strongest social ties to geographically and economically comparable weaker ties, thereby changing peer-county identities. The dependent variable is the change in (small bank) rates of deposits of different sizes and maturities (6m10K, 12m10k, and 12m100k). Estimation method is 2SLS with county and time fixed effects. The lower part of the table also reports the number of observations and the Kleibergen-Paap under-identification statistic. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) 6m10K	(2) 12m10K	(3) 12m100K	(4) 6m10K	(5) 12m10K	(6) 12m100K
Placebo SDR	0.268	0.106	0.027	0.162	0.160	0.040
	(0.173)	(0.180)	(0.166)	(0.293)	(0.565)	(0.396)
Placebo SDR × High FSoph				0.035	-0.017	-0.004
				(0.059)	(0.122)	(0.081)
DDR	0.053*	0.058***	0.062***	0.073	0.051	0.060
	(0.031)	(0.020)	(0.021)	(0.053)	(0.070)	(0.055)
EPDR	0.454	0.107	-0.053	0.247	0.213	-0.028
	(0.389)	(0.401)	(0.369)	(0.608)	(1.154)	(0.812)
LBMS	0.288	0.223	0.186	0.276	0.228	0.187
	(0.194)	(0.217)	(0.219)	(0.185)	(0.242)	(0.227)
SBHHI	-0.188	0.047	0.190	-0.058	-0.043	0.170
	(0.382)	(0.507)	(0.485)	(0.487)	(1.117)	(0.835)
Deposit_pc	0.007	-0.001	-0.006	0.004	0.001	-0.006
	(0.009)	(0.012)	(0.012)	(0.012)	(0.027)	(0.020)
Seniors	0.437	-1.706	-2.066	-0.328	-1.256	-1.957
	(1.676)	(1.755)	(1.717)	(2.155)	(4.535)	(3.325)
Population	0.011	-0.010	-0.012	0.007	-0.007	-0.011
	(0.013)	(0.014)	(0.013)	(0.016)	(0.031)	(0.023)
Realgdppc	0.000	0.002*	0.002**	0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
FSoph	-0.002	0.013	0.021	0.011	0.005	0.019
	(0.025)	(0.029)	(0.031)	(0.036)	(0.085)	(0.068)
Obs.	17,234	17,263	17,224	17,234	17,263	17,224
Kl.-Paap rk LM	3.1*	1.6	1.9	1.0	0.2	0.4

Table 5. Use of social media and uniform pricing

The table reports coefficient estimates and standard errors (in parentheses) from panel β-convergence regressions. The dependent variable is the change in the gap between deposit rates of different sizes and maturities (6m10K, 12m10k, and 12m100k) and the weighted average of deposit rates of social peers. Columns (1)–(3) report results for small banks, while columns (4)–(6) report results for large banks. The social-peer rate is constructed using only SCI-connected counties located more than 25 miles from the focal county. Estimation method is OLS with time and county fixed effects. The data frequency is quarterly and the sample period is 2011q2-2023q3. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) 6m10K	(2) 12m10K	(3) 12m100K	(4) 6m10K	(5) 12m10K	(6) 12m100K
$SC \times (r_{c,t-1} - r^{sc}_{c,t-1})$	-0.002***	-0.001***	-0.001***	-0.001*	-0.001*	-0.002***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
$(r_{c,t-1} - r^{sc}_{c,t-1})$	-0.080***	-0.098***	-0.081***	-0.057***	-0.103***	-0.090***
	(0.005)	(0.004)	(0.004)	(0.006)	(0.005)	(0.004)
SC	0.001***	0.001**	0.001**	0.001***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SBHHI	-0.016**	-0.021**	-0.024***	-0.001	-0.006	-0.006
	(0.006)	(0.008)	(0.008)	(0.003)	(0.004)	(0.005)
LBMS	0.004	0.013*	0.006	0.005	0.006*	0.010**
	(0.006)	(0.007)	(0.007)	(0.003)	(0.004)	(0.005)
Deposit_pc	0.000***	0.000*	0.000***	0.000	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Seniors	-0.164***	-0.156***	-0.161***	0.009	0.048	0.083*
	(0.042)	(0.050)	(0.052)	(0.028)	(0.038)	(0.048)
Population	0.009	0.014	0.014	0.048***	0.025***	0.047***
	(0.008)	(0.009)	(0.010)	(0.005)	(0.006)	(0.008)
Realgdppc	0.000	0.000	0.000	0.000**	0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FSophistication	0.000	-0.000	-0.002	-0.001*	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-0.012	-0.034	-0.033	-0.207***	-0.124***	-0.225***
	(0.032)	(0.037)	(0.038)	(0.022)	(0.029)	(0.036)
Obs.	143,461	143,555	144,811	91,068	91,079	91,826
R-squared	0.054	0.056	0.047	0.039	0.082	0.065

Appendix A: Theory model

Model setup

Environment. Consider two counties, A and B. County A experiences an exogenous *shock* that increases local deposit rates by Δr_A. The event generates social-media *buzz* of intensity $\mu_A > 0$. We focus on the implications of such a shock for county B's deposit market with $N_B \geq 2$ symmetric small banks that compete in deposit rates under differentiated-product Bertrand competition.

Depositors in county B. A unit mass of depositors resides in county B. A share λ are *sophisticated* and face a low search cost $c_L > 0$. The remaining share $1 - \lambda$ are *non-sophisticated* with a higher search cost $c_H > c_L$. Each depositor decides whether to *search* for better deposit rates among local banks. Searching allows a depositor to observe and compare the offers of all N_B banks. As a result, searching depositors become sensitive to differences in rates across banks and are willing to switch to a bank offering a slightly higher rate. So, searching turns previously "captive" depositors into contestable customers.

However, depositors face an attention friction – it is costly to keep track of market conditions, and unless something salient happens, they do not update (Reis 2006). Therefore, when no salient exposure arrives in county B depositors remain inattentive and do not initiate search. Let us denote $m \in [0, 1]$ the fraction of depositors who search, which is endogenous and depends on the salient exposure and subsequent choice of depositors to search (taking into account the search cost). Then the substitutability of deposits across banks, and hence the elasticity of each bank's deposit supply, increases with m.

Buzz generation and awareness. An exogenous event in county A—such as a local shock to deposit rates of magnitude Δr_A—generates social-media activity or *buzz* of the intensity μ_A. Each depositor in county B is connected to residents of A through social media. Let $w_{BA} \in [0, 1]$ denote the *social connectedness index* between the two counties. The number of buzz-related posts seen by a representative depositor in B is assumed to

follow a Poisson distribution with mean

$$\mu_A = \alpha \, w_{BA} \, \Delta r_A, \tag{1}$$

where $\alpha > 0$ captures the overall visibility of financial content on the platform.

Depositors become *aware* of the event if they encounter at least one such post. Hence, the probability of awareness is

$$p(\mu_A) = p(w_{BA}, \Delta r_A) = 1 - \exp[-\alpha \, w_{BA} \, \Delta r_A]. \tag{2}$$

This probability increases in both the social connectedness w_{BA} and the magnitude of the originating shock Δr_A, approaching one as the event becomes highly salient or widely shared.

Banks. In county B, each of its N_B banks offers a deposit rate r_i and attracts a volume of deposits

$$D_i = a + b \, r_i - d(m) \, \bar{r}_{-i}, \qquad d(m) = d_0 + d_1 \, m, \; d_1 > 0, \tag{3}$$

where $\bar{r}_{-i}$ is the average rate of competitors and $m \in [0, 1]$ is the share of depositors who actively search. Deposit supply to bank i is increasing in its own posted rate and decreasing in the rates of its rivals, as in a differentiated-product (Bertrand) model of imperfectly competitive deposit pricing: b is own-rate sensitivity and $d(m)$ the cross-bank substitutability of deposits.[24]. Search operates through the cross-rate term $d(m)$: an aware depositor who searches compares all offers and becomes responsive to rate differences across banks, so a larger searching share m raises cross-bank substitutability $d(m) = d_0 + d_1 m$. The baseline level $d_0 \geq 0$ is the substitutability among non-searching ("captive") depositors; $d_1 > 0$ is the marginal effect of search. As deposits become more substitutable across banks, competition for depositors intensifies and small banks raise their rates.

Banks choose deposit rates to maximize their return $\Pi_i = (R - r_i)D_i$, where R is the

[24] Differentiation among bank products might be related to the additional services offered in a bundle together with deposits, for instance liquidity services, as well as convenience (branch proximity, digital access), trust, brand reputation, service quality, and perceived safety).

return on bank assets. Throughout we maintain $b > d(m)$[25] And the assumption

$$bR > a, \tag{4}$$

which guarantees a positive equilibrium rate marked *down* from the loan return R—that is, positive oligopsony rent for competition to erode.

Timeline.

- At $t = 0$: First, a shock to deposit rate in county A occurs Δr_A, creating social-media buzz of intensity μ_A. Second, the buzz diffuses to county B according to the connectedness w_{BA}. Each depositor becomes aware with probability $p(w_{BA}, \Delta r_A)$.
- At $t = 1$: Aware depositors decide whether to incur their search cost (c_L or c_H) to compare banks' rates. The resulting share of active searchers is m.
- At $t = 2$: Given m, the N_B banks simultaneously set deposit rates in a differentiated Bertrand game. Depositors choose banks accordingly.

No-buzz benchmark (inattention). When no salient exposure arrives in county B, depositors remain inattentive and do not initiate search. Hence, the share of active searchers is $m = 0$. With $m = 0$, banks face baseline substitutability d_0 and post the baseline rate

$$r = r_0,$$

to which inattentive depositors are locked absent search, staying in their default or incumbent accounts.

Therefore, in equilibrium, the baseline rate must satisfy

$$r_0 \equiv r^*(0) = \frac{bR - a}{2b - d_0}.$$

In this benchmark, parameters governing search activation or pass-through, the sophis-

[25] We maintain $b > d_0 + d_1$, so that a bank's own-rate sensitivity exceeds cross-rate sensitivity even at maximal search ($m = 1$, where $d(m) = d_0 + d_1$ is largest). This condition ensures an interior symmetric equilibrium in linear Bertrand competition: it keeps the denominator $2b - d(m)$ in the equilibrium rate strictly positive, and guarantees a positive supply of deposits, $D_i = a + (b - d(m))\, r^* > 0$. Economically, it requires that banks retain some product differentiation even when depositors search intensively: deposits never become perfect substitutes across banks.

tication share λ, search costs (c_L, c_H), do not affect outcomes because they operate only through m, which is zero in the absence of buzz.

Equilibrium

We solve the model by backward induction. We first characterize banks' equilibrium deposit rates given the fraction of active searchers m, then derive depositors' optimal search decision. Finally, we explore how social interconnectedness, depositors' financial sophistication and deposit market competition affect the equilibrium.

Deposit market equilibrium

Given an exogenous fraction m of active depositors, each of the N_B symmetric banks in county B chooses its deposit rate r_i to maximize

$$\Pi_i = (R - r_i)\big(a + br_i - d(m)\,\bar{r}_{-i}\big).$$

The first-order condition for an interior symmetric equilibrium ($r_i = \bar{r}_{-i} = r$) yields

$$(2b - d(m))\,r = bR - a. \tag{5}$$

Hence, the equilibrium rate is

$$r^*(m) = \frac{bR - a}{2b - d(m)} \tag{6}$$

Proposition 1 (Deposit-market equilibrium)**.** *For a given fraction m of active searchers, the equilibrium deposit rate is increasing in m:*

$$\frac{\partial r^*(m)}{\partial m} = \frac{d_1\,(bR - a)}{\big(2b - d(m)\big)^2} > 0.$$

Intuitively, more search raises cross-bank substitutability $d(m)$, which erodes banks' oligopsony markdown and raises equilibrium deposit rates.

Depositors' search behavior

Depositors' search behavior. Aware depositors can search to obtain the competitive rate $r^*(m)$ rather than the inattentive benchmark r_0, treating the aggregate search intensity m as given. In the no-buzz benchmark, no depositor searches, $m = 0$, and banks post the baseline rate $r = r_0$.

The expected benefit from search is therefore

$$V(m) = \beta\big[r^*(m) - r_0\big] = \beta\left[\frac{bR-a}{2b-d(m)} - \frac{bR-a}{2b-d_0}\right],$$

where $\beta \in (0,1]$ captures the perceived gain per unit of rate improvement. Under (4), $V(0) = 0$, and $V(m)$ is increasing in m. Sophisticated depositors with cost c_L and non-sophisticated ones with cost $c_H > c_L$ search if

$$V(m) \geq c_j, \qquad j \in \{L, H\}.$$

Given the probability of awareness $p \equiv p(w_{BA}, \Delta r_A)$, the aggregate share of searchers satisfies

$$m = p\left[\lambda \mathbf{1}\left\{V(m) \geq c_L\right\} + (1-\lambda)\mathbf{1}\left\{V(m) \geq c_H\right\}\right]. \tag{7}$$

Equation (7) makes clear that depositors' search decisions are strategic complements: if more depositors search, banks raise deposit rates, which in turn makes search more attractive to other aware depositors. As a result, the model may admit multiple self-fulfilling search equilibria.

Proposition 2 (Search equilibria and coordination)**.** *The model always admits a zero-search equilibrium, $m^* = 0$. In addition, one or more positive-search equilibria may exist.*

An equilibrium with only sophisticated depositors searching, $m^* = p\lambda$, exists if

$$c_L \leq V(p\lambda) < c_H \tag{8}$$

An equilibrium with all aware depositors searching, $m^* = p$, exists if

$$V(p) \geq c_H \tag{9}$$

Proof. Since $r_0 = r^*(0)$, the gain from search is zero when nobody searches. Therefore, if depositors expect no one else to search, search is not privately worthwhile and $m^* = 0$ is always an equilibrium.

A positive-search equilibrium can take one of two forms. First, only sophisticated depositors search $m^* = p\lambda$. For this to be an equilibrium, sophisticated depositors must find search worthwhile, while non-sophisticated depositors must not. Using (6) this requires $c_L \leq V(p\lambda) < c_H$, which is equivalent to (8).

Second, all aware depositors search $m^* = p$. For this to be an equilibrium, even non-sophisticated depositors must find search worthwhile. This requires $V(p) \geq c_H$, which is equivalent to (9).

Because V is increasing, each condition defines a threshold in the awareness probability p. Let $G \equiv \beta(bR - a) > 0$ and $s \equiv 2b - d_0 > 0$. Solving $V(p_A\lambda) = c_L$, $V(p_B\lambda) = c_H$, and

$V(p_C) = c_H$ for p gives

$$p_A = \frac{c_L\, s^2}{d_1\, \lambda\, (G + c_L s)}, \qquad p_B = \frac{c_H\, s^2}{d_1\, \lambda\, (G + c_H s)}, \qquad p_C = \frac{c_H\, s^2}{d_1\, (G + c_H s)}.$$

The partial equilibrium exists $m^* = p\lambda$ for $p \in [p_A, p_B)$ and the full equilibrium $m^* = p$ for $p \geq p_C$. Since $p_C = \lambda\, p_B$, $p_C < p_B$; together with $m^* = 0$, the number of equilibria therefore grows from one (only $m^* = 0$, at low p) to two and then three as awareness rises. Which of the partial and full equilibria appears first depends on the share of sophisticated depositors: $p_A < p_C$ when λ is large and $p_C < p_A$ when λ is small. Generically, then, the model has either a unique no-search equilibrium or, in addition, one or two positive-search equilibria. □

Two implications are worth emphasizing. First, search is not triggered by awareness alone. Awareness brings depositors to the decision node, but whether they search depends on whether the induced increase in equilibrium deposit rates is sufficient to cover search costs.

Second, because $m = 0$ always exists, positive search requires a coordination device in beliefs: a positive-search equilibrium $m^* > 0$ arises only if aware depositors expect enough other aware depositors to search. This coordination force is stronger when social connectedness w_{BA}, the size of the originating shock Δr_A, or platform visibility α raise awareness, and when stronger competition amplifies the pass-through from search to deposit rates.

Combining (6) with $m^*(w_{BA}, \lambda) \in \{0, p\lambda, p\}$ from Proposition 2, and conditional on selection of a positive-search equilibrium, the equilibrium deposit rate in county B is

$$r_B^*(w_{BA}, \lambda) = \frac{bR - a}{2b - d\big(m^*(w_{BA}, \lambda)\big)}. \tag{10}$$

Thus, socially connected shocks affect deposit rates only if they move the economy from the zero-search equilibrium to a positive-search equilibrium or within a positive-search equilibrium raise the awareness probability p and thereby the mass of searching depositors.

Comparative statics

Next, we focus on how model parameters affect the size of the deposit-rate response, conditional on the economy being in a positive-search equilibrium.

Proposition 3 (Financial sophistication)**.** *Higher financial sophistication λ weakly enlarges the set of parameters for which a positive-search equilibrium $m^* > 0$ exists. Moreover, conditional on selection of a positive-search equilibrium, higher λ weakly raises the post-buzz equilibrium deposit rate r^* in county B.*

Proof of Proposition 3. By Proposition 2, the partial-participation equilibrium exists for $p \in [p_A, p_B)$ and the full-participation equilibrium for $p \geq p_C$. Since $p_C = \lambda p_B \leq p_B$, these regions overlap, so a positive-search equilibrium exists for all $p \geq \min(p_A, p_C)$. As p_A is strictly decreasing in λ while p_C is independent of λ, the lower endpoint $\min(p_A, p_C)$ is weakly decreasing in λ. Hence higher λ weakly enlarges the set of awareness levels for which a positive-search equilibrium exists.

A higher λ weakly raises the associated equilibrium deposit rate because it weakly increases the equilibrium mass of searchers with partial participation $m^* = p\lambda$, while leaving r^* unchanged in the equilibrium with full participation $m^* = p$. □

Higher connectedness w_{BA} raises the probability of awareness and expands the mass of active searchers. A larger share of sophisticated depositors λ reduces the average search cost, amplifying the behavioral response to social-media buzz.

Proposition 4 (Buzz spillover)**.** *Consider only positive-search equilibria. Higher social connectedness w_{BA}, and a larger originating deposit-rate shock Δr_A weakly enlarge the set of parameters for which a positive-search equilibrium $m^* > 0$ exists. Conditional on a positive-search equilibrium $m^* > 0$ being selected, both parameters raise the post-buzz equilibrium deposit rate r^* in county B.*

Proof of Proposition 4. Recall that awareness is given by (2). Therefore,

$$\frac{\partial p}{\partial w_{BA}} = \alpha \Delta r_A \exp(-\alpha w_{BA} \Delta r_A) \geq 0 \quad \text{and} \quad \frac{\partial p}{\partial \Delta r_A} = \alpha w_{BA} \exp(-\alpha w_{BA} \Delta r_A) \geq 0.$$

By Proposition 2, a positive-search equilibrium exists if either (8) or (9). Since both thresholds are increasing in p, higher social connectedness w_{BA} or a larger shock Δr_A weakly enlarge the set of parameters for which a positive-search equilibrium exists.

Conditional on a positive-search equilibrium being selected, the equilibrium deposit rate (10) depends on w_{BA} and Δr_A only through m^*. Both positive-search values $m^* \in \{p\lambda, p\}$ increase in awareness p, so r^* increases in p. Since p increases in w_{BA} and Δr_A, both parameters raise r^*. □

More salient and stronger shocks in county A generate higher awareness in B and thus higher local deposit rates. Social-media channels therefore transmit financial shocks across markets even in the absence of balance-sheet linkages.

To sum up, the equilibrium exhibits *socially mediated deposit competition*. A shock that raises deposit rates in one county triggers social-media buzz, which increases awareness and can trigger search in socially connected counties. Higher awareness can raise the

share of active depositors, intensifying local competition and deposit-rate pass-through. The strength of this mechanism depends on (i) the degree of social connectedness across locations, and (ii) the share of financially sophisticated depositors.

Appendix B: Additional information on data

Table B1. Summary statistics of deposit rates (Δ: time-difference)

	Small Banks Δr			Large Banks Δr		
Stats	6m10K	12m10K	12m100K	6m10K	12m10K	12m100K
N	23,216	23,246	23,205	14,233	14,223	14,151
Mean	0.157	0.189	0.193	0.045	0.040	0.059
SD	0.439	0.537	0.553	0.197	0.246	0.303
p1	-0.675	-0.886	-0.916	-0.340	-0.650	-0.750
p50	0.023	0.035	0.038	0.000	0.000	0.000
p99	1.848	1.996	2.028	1.049	1.065	1.200

Table B2. Summary statistics of SCI-weighted deposit rates and large-bank closure exposure (Δ: time-difference)

	Areas > 25 miles				Areas > 25 miles & top 10% SCI links			
Stats	6m10K	12m10K	12m100K	SLBC	6m10K	12m10K	12m100K	SLBC
N	23,392	23,392	23,392	23,392	23,392	23,392	23,392	23,392
Mean	0.485	0.579	0.592	0.085	0.424	0.504	0.516	0.055
SD	1.385	1.727	1.778	0.071	1.289	1.591	1.640	0.068
p1	-2.316	-3.265	-3.352	0.018	-2.160	-3.034	-3.116	0.000
p50	0.071	0.100	0.103	0.061	0.051	0.073	0.074	0.030
p99	6.906	8.298	8.523	0.391	6.640	7.837	8.084	0.357

Table B3. Summary statistics of control variables (Δ: time-difference)

Stats	**ΔSBHHI**	**ΔFsophistication**	**ΔDeposit_pc**	**ΔRealgdppc**	**ΔPopulation**	**ΔSeniors**	**ΔLBMS**	**LBC**
N	23,392	23,392	23,392	23,392	23,392	23,392	23,392	23,392
Mean	0.002	0.106	1.107	0.598	0.569	0.004	0.002	0.092
SD	0.020	0.195	2.334	3.985	2.088	0.003	0.022	0.289
p1	-0.065	-0.425	-5.300	-14.320	-1.814	-0.003	-0.083	0.000
p50	0.000	0.093	0.704	0.431	0.013	0.004	0.000	0.000
p99	0.097	0.662	10.665	18.983	13.297	0.012	0.104	1.000

Table B4. Variable definitions

Variable	Definition
$\Delta r_{c,t}$	Annual change in the average deposit rate offered by banks of the indicated size and deposit product in county c.
$\Delta LBMS_{c,t}$	Decline in the deposit-market share of large banks in county c, defined as the negative of the annual change in their market share.
$LBC_{c,t}$	Annual number of county-quarter merger-related large-bank branch-closure events in county c.
$SCI^{*}_{c,j}$	Normalized Social Connectedness Index between counties c and j, based on the intensity of Facebook friendship links between their residents.
$SDR_{c,t}$	SCI-weighted sum of deposit-rate changes in peer counties. In the baseline specification, the focal county and peer counties located within 25 miles are excluded.
$SLBC_{c,t}$	SCI-weighted sum of merger-related large-bank closure events in peer counties, constructed using the same county links as $SDR_{c,t}$.
$DDR_{c,t}$	Inverse-distance-weighted sum of deposit-rate changes in peer counties.
$EPDR_{c,t}$	Economic-proximity-weighted sum of deposit-rate changes in peer counties, where economic proximity is measured by the cosine similarity of county industry-employment shares.
$SBHHI_{c,t}$	Herfindahl–Hirschman Index of deposit-market concentration among small banks operating in county c.
$Depositpc_{c,t}$	Total deposits held at bank branches in county c, divided by county population.
$Realgdppc_{c,t}$	Real gross domestic product per capita in county c.
$Seniors_{c,t}$	Share of the county population aged 65 or older.
$Population_{c,t}$	Total county population, measured in thousands.
$FSophistication_{c,t}$	County financial-sophistication index, defined as the first principal component of seven educational-attainment shares and the shares of tax returns reporting dividend income and capital gains. Higher values indicate greater financial sophistication.
$HighFSoph_{c}$	Indicator equal to one when the county's time-averaged financial-sophistication index is above the cross-county median, and zero otherwise.

Appendix C: Branch closure data

Our starting point is the FFIEC/FDIC branch-office closing file, which records each branch's identity, effective closing date, and affiliated banking organization. We combine these data with the FDIC Summary of Deposits branch file and RateWatch branch-level deposit-rate data to assign each branch to a bank, a county market, and a calendar period.

We classify a bank as *large* using the definition described in the main analysis. We then identify *merger-linked* branch closures by matching branches to FFIEC transformation records and retaining closures that occur within two years of a merger involving the affiliated bank. This procedure isolates the set of branch closures most relevant for our empirical design, since these closures are plausibly driven by consolidation rather than by local economic conditions.

Table C1. Large-bank branch closures.

Period	Affected counties	Period	Affected counties
2016q1	49	2020q1	101
2016q2	60	2020q2	130
2016q3	121	2020q3	35
2016q4	147	2020q4	248
2017q1	57	2021q1	390
2017q2	51	2021q2	335
2017q3	162	2021q3	205
2017q4	159	2021q4	308
2018q1	11	2022q1	216
2018q2	88	2022q2	124
2018q3	19	2022q3	111
2018q4	111	2022q4	88
2019q1	91	2023q1	197
2019q2	203	2023q2	275
2019q3	142	2023q3	137
2019q4	94		
		Total	4,465

The resulting distribution indicates that merger-linked large-bank branch closures are economically meaningful and sufficiently common for empirical analysis. Table C1 reports the quarterly distribution of county observations affected by at least one large-bank merger-linked branch closure. Across the sample, there are 4,465 affected county-quarter

Table C2. Annual exposure to large-bank branch closures.

Time	Affected counties	Affected counties (%)
2016	203	6.90
2017	278	9.50
2018	277	9.50
2019	270	9.20
2020	392	13.40
2021	331	11.30
2022	234	8.00
2023	170	5.80
Total	2,155	9.20

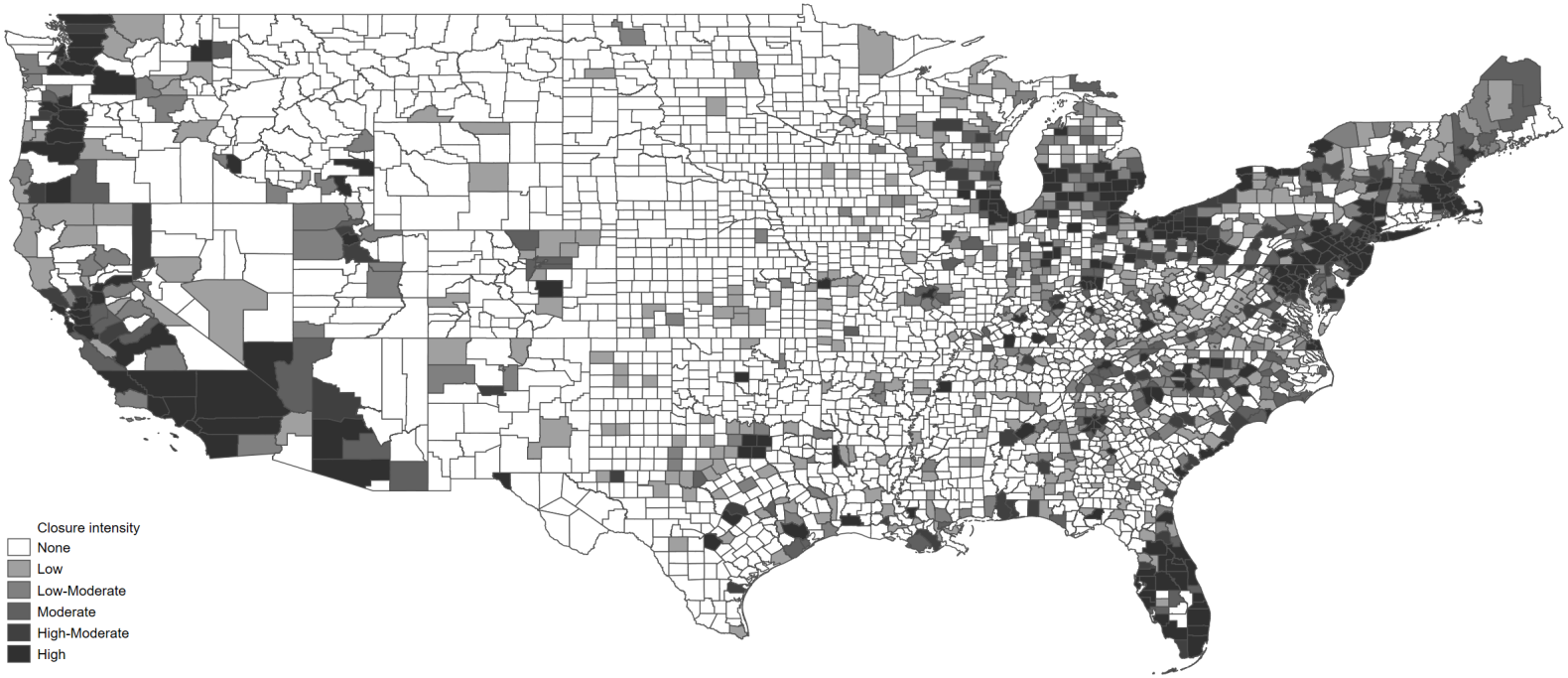
observations. These events are broadly distributed over time rather than concentrated in only a few periods.

For the main analysis, we define $LBC_{j,t}$ as an indicator equal to one if county j experiences at least one merger-linked large-bank branch closure during year t. Table C2 summarizes the annual distribution of these events. On average, 2,155 county-year observations are affected over the sample, corresponding to 9.20% of counties per year. The annual incidence varies over time, from 5.80% in 2023 to 13.40% in 2020, confirming that the identifying variation is not driven by a small number of isolated events.

Figure C1 presents a branch-closure intensity map of US counties. To obtain the counties exposure to over time, we produce an aggregate measure equal to the number of periods in which branch closures of large-banks involved to mergers occurred. The resulting variable is then grouped into five categorical bins. The spatial pattern reveals substantial heterogeneity in closure intensity across counties.

Overall, the branch-closure data provide broad geographic and temporal coverage and allow us to identify plausibly exogenous local disruptions in branch presence associated with bank consolidation. This distinction is central to the empirical design because it separates merger-related contraction in local branch networks from other forms of branch adjustment.

Figure C1. *Branch closures* of large banks involved in a merger.
The map shows the number of year–quarter periods in which a county experienced at least one merger-related large bank branch closure over the sample period. Counties are shaded from white (no closures) to dark gray (10% or more closure periods).



Appendix D: Further robustness tests

Table D1. Counties without large banks

The table reports coefficient estimates and standard errors (in parentheses) from second stage regressions. The sample is restricted to counties without any large-bank branches. The social-connection measures are constructed using only SCI-connected counties located more than 25 miles from the focal county. The dependent variable is the change in (small bank) rates of deposits of different sizes and maturities (6m10K, 12m10k, and 12m100k). Estimation method is 2SLS with county and time fixed effects. The lower part of the table also reports the number of observations and the Kleibergen-Paap underidentification statistic. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) 6m10K	(2) 12m10K	(3) 12m100K	(4) 6m10K	(5) 12m10K	(6) 12m100K
SDR	0.076***	0.068***	0.061**	-0.009	0.005	0.006
	(0.023)	(0.023)	(0.026)	(0.041)	(0.038)	(0.046)
SDR × High FSoph				0.083***	0.061**	0.052
				(0.031)	(0.028)	(0.032)
DDR	0.075***	0.064***	0.060***	0.088***	0.073***	0.067***
	(0.016)	(0.015)	(0.015)	(0.018)	(0.016)	(0.016)
EPDR	0.152*	0.160**	0.156**	0.008	0.057	0.065
	(0.086)	(0.076)	(0.078)	(0.112)	(0.096)	(0.106)
SBHHI	0.337	0.402	0.311	0.329	0.384	0.295
	(0.232)	(0.279)	(0.290)	(0.259)	(0.300)	(0.307)
Deposit_pc	0.002	0.002	0.001	0.003	0.003	0.002
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
Seniors	0.823	0.597	0.654	-0.381	-0.382	-0.228
	(1.544)	(1.749)	(1.799)	(1.726)	(1.885)	(1.950)
Population	0.063**	0.093***	0.093***	0.072**	0.100***	0.098***
	(0.030)	(0.033)	(0.033)	(0.032)	(0.035)	(0.035)
Realgdppc	0.000	0.001	0.001	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
FSoph	0.016	0.024	0.025	0.025	0.033	0.033
	(0.017)	(0.020)	(0.020)	(0.018)	(0.021)	(0.021)
Obs.	6,954	6,972	6,942	6,954	6,972	6,942
Kl.-Paap rk LM	141.3***	130.8***	121.5***	80.0***	83.4***	79.3***

Table D2. Social connections and small bank deposit rate changes: census division-year fixed effects

The table reports coefficient estimates and standard errors (in parentheses) from second stage regressions. The social-connection measures are constructed using only SCI-connected counties located more than 25 miles from the focal county. The dependent variable is the change in (small bank) rates of deposits of different sizes and maturities (6m10K, 12m10k, and 12m100k). Estimation method is 2SLS with county and time-by-census-division fixed effects. The lower part of the table also reports the number of observations and the Kleibergen-Paap under-identification statistic. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) 6m10K	(2) 12m10K	(3) 12m100K	(4) 6m10K	(5) 12m10K	(6) 12m100K
SDR	0.043	0.111	0.094	-0.053	0.042	0.027
	(0.083)	(0.077)	(0.087)	(0.088)	(0.081)	(0.094)
SDR × *High FSoph*				0.104***	0.077***	0.073***
				(0.028)	(0.026)	(0.026)
DDR	0.065*	0.097***	0.082**	0.083**	0.113***	0.096**
	(0.039)	(0.032)	(0.040)	(0.042)	(0.034)	(0.041)
EPDR	0.066	0.181	0.163	-0.048	0.102	0.085
	(0.154)	(0.147)	(0.159)	(0.162)	(0.151)	(0.167)
LBMS	0.032	0.131	0.121	0.092	0.203	0.189
	(0.177)	(0.205)	(0.215)	(0.187)	(0.214)	(0.222)
SBHHI	0.151	-0.018	-0.054	0.118	-0.055	-0.091
	(0.162)	(0.201)	(0.216)	(0.171)	(0.207)	(0.221)
Deposit_pc	-0.002	0.000	-0.000	-0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Seniors	0.510	0.055	-0.069	-0.764	-1.037	-1.162
	(1.167)	(1.386)	(1.403)	(1.266)	(1.472)	(1.499)
Population	-0.003	0.000	0.003	-0.007	-0.003	-0.001
	(0.007)	(0.009)	(0.009)	(0.007)	(0.009)	(0.009)
Realgdppc	0.000	0.001	0.001	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
FSoph	0.014	0.008	0.007	0.028*	0.022	0.021
	(0.015)	(0.019)	(0.020)	(0.016)	(0.019)	(0.021)
Obs.	17,234	17,263	17,224	17,234	17,263	17,224
Kl.-Paap rk LM	21.2***	22.5***	17.4***	21.3***	22.4***	17.1***

Table D3. Social connections and small bank deposit rate changes: 50-mile exclusion

The table reports coefficient estimates and standard errors (in parentheses) from second stage regressions. The social-connection measures are constructed using only SCI-connected counties located more than 50 miles from the focal county. The dependent variable is the change in (small bank) rates of deposits of different sizes and maturities (6m10K, 12m10k, and 12m100k). Estimation method is 2SLS with county and time fixed effects. The lower part of the table also reports the number of observations and the Kleibergen-Paap under-identification statistic. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) 6m10K	(2) 12m10K	(3) 12m100K	(4) 6m10K	(5) 12m10K	(6) 12m100K
SDR	0.171***	0.157***	0.145***	0.126***	0.119***	0.114***
	(0.024)	(0.024)	(0.024)	(0.040)	(0.040)	(0.041)
SDR × *High FSoph*				0.047*	0.039	0.032
				(0.028)	(0.026)	(0.027)
DDR	0.093***	0.073***	0.068***	0.099***	0.077***	0.071***
	(0.008)	(0.007)	(0.008)	(0.009)	(0.008)	(0.008)
EPDR	0.135**	0.120**	0.111*	0.090	0.084	0.082
	(0.061)	(0.057)	(0.057)	(0.072)	(0.068)	(0.069)
LBMS	0.227	0.261	0.263	0.250	0.286	0.284
	(0.153)	(0.188)	(0.189)	(0.154)	(0.189)	(0.191)
SBHHI	0.101	0.032	-0.014	0.080	0.007	-0.035
	(0.151)	(0.185)	(0.190)	(0.153)	(0.186)	(0.191)
Deposit_pc	-0.000	-0.000	-0.001	0.000	0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Seniors	0.265	-1.130	-1.223	-0.233	-1.603	-1.619
	(1.212)	(1.390)	(1.428)	(1.255)	(1.444)	(1.482)
Population	-0.000	-0.011	-0.009	0.000	-0.011	-0.009
	(0.006)	(0.008)	(0.008)	(0.006)	(0.008)	(0.008)
Realgdppc	0.001	0.001*	0.001*	0.001*	0.001*	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
FSoph	0.019	0.018	0.016	0.023*	0.023	0.020
	(0.013)	(0.015)	(0.016)	(0.013)	(0.016)	(0.016)
Obs.	17,234	17,263	17,224	17,234	17,263	17,224
Kl.-Paap rk LM	491.6***	433.7***	425.0***	333.4***	312.4***	302.9***

Table D4. First-stage regressions for social connections and small bank deposit rate changes

The table reports coefficient estimates and county-clustered standard errors (in parentheses) from first-stage regressions. Columns (1)–(3) report the first stage for the *Social Deposit Rate* constructed using SCI-connected counties located more than 25 miles from the focal county. Columns (4)–(6) report the corresponding first stage using the sparse SCI measure, which keeps only the strongest 10% of non-local SCI links. Estimation method is OLS with county and time fixed effects. The lower part of the table also reports the number of observations, R-squared, and the F-test of excluded instruments. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) 6m10K	(2) 12m10K	(3) 12m100K	(4) 6m10K	(5) 12m10K	(6) 12m100K
SLBC	2.424***	2.772***	2.792***	2.292***	2.625***	2.641***
	(0.139)	(0.166)	(0.173)	(0.135)	(0.162)	(0.169)
DDR	0.235***	0.155***	0.162***	0.218***	0.142***	0.148***
	(0.032)	(0.033)	(0.033)	(0.031)	(0.032)	(0.032)
EPDR	-2.468***	-2.455***	-2.420***	-2.438***	-2.387***	-2.360***
	(0.240)	(0.239)	(0.238)	(0.238)	(0.233)	(0.233)
LBMS	-0.902*	-1.167**	-1.225**	-0.878*	-1.134**	-1.193**
	(0.464)	(0.581)	(0.600)	(0.452)	(0.561)	(0.580)
SBHHI	2.387***	3.205***	3.280***	2.271***	3.048***	3.117***
	(0.459)	(0.585)	(0.601)	(0.452)	(0.571)	(0.588)
Deposit_pc	-0.061***	-0.079***	-0.081***	-0.059***	-0.076***	-0.078***
	(0.008)	(0.010)	(0.010)	(0.008)	(0.009)	(0.010)
Seniors	-4.528	-7.770	-7.135	-3.820	-7.091	-6.389
	(5.420)	(6.697)	(6.924)	(5.351)	(6.523)	(6.762)
Population	-0.046**	-0.055**	-0.055**	-0.049**	-0.059**	-0.059**
	(0.020)	(0.025)	(0.025)	(0.019)	(0.024)	(0.025)
Realgdppc	0.004*	0.005	0.005	0.004*	0.004	0.005
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
FSoph	0.155***	0.181***	0.190***	0.160***	0.185***	0.193***
	(0.048)	(0.059)	(0.060)	(0.047)	(0.057)	(0.059)
Constant	1.278***	1.658***	1.670***	1.284***	1.635***	1.651***
	(0.105)	(0.127)	(0.130)	(0.104)	(0.124)	(0.127)
Obs.	17,234	17,263	17,224	17,234	17,263	17,224
R-squared	0.658	0.660	0.662	0.621	0.624	0.625
F-test excl. instr.	305.4***	278.3***	260.2***	286.9***	263.2***	244.6***

Appendix E: Principal components analysis - Financial sophistication

County-level financial sophistication is a latent construct that cannot be observed directly. We therefore rely on observable characteristics that are plausibly associated with this underlying trait. We draw on two county-level data sources. First, educational attainment is measured by the shares of the population aged 25 years or older in seven mutually exclusive categories: less than ninth grade; ninth to twelfth grade with no diploma; high-school graduate, including equivalency; some college with no degree; associate's degree; bachelor's degree; and graduate or professional degree. Second, participation in financial markets is proxied by the shares of tax returns reporting dividend income and capital gains, obtained from the IRS Statistics of Income.[26]

These nine variables are strongly interrelated and collectively capture different dimensions of the population's financial knowledge and engagement with financial markets. Including all nine variables directly in the empirical analysis would introduce substantial multicollinearity and make it difficult to summarize their common variation. We therefore use principal components analysis to construct a parsimonious county-level measure of financial sophistication.

Figure E1 presents the scree plot of the PCA eigenvalues. The first component has an eigenvalue of 4.563 and explains 50.7% of the total standardized variance. The second and third components have eigenvalues of 1.547 and 1.076 and explain an additional 17.2% and 12.0%, respectively. Together, the first three components account for approximately 79.8% of the total variance. The fourth component has an eigenvalue of 0.642, below the conventional Kaiser threshold of one, indicating that the first three components contain the principal systematic dimensions of variation in the underlying variables. Table E1 reports the eigenvalues and explained variance of the first four components.

Table E2 presents the loadings of the first three components. The first component has negative loadings on the three lowest educational-attainment categories and positive

[26] Because IRS data on dividend income and capital gains are available only through 2022, we extrapolate the corresponding 2023 county-level participation measures using county-specific linear trends.

loadings on college education, associate's, bachelor's, and graduate degrees, as well as on dividend income and capital gains. In particular, the largest positive loadings are associated with bachelor's degrees, dividend income, capital gains, and graduate degrees. The component therefore takes higher values in counties with more highly educated populations and greater participation in financial markets. We accordingly interpret the first component as a measure of county-level financial sophistication and use it in the empirical analysis.

The second component places positive weight on high-school graduates, some college education, and associate's degrees, while assigning negative weights to both lower educational attainment and bachelor's and graduate degrees. It therefore appears to capture the concentration of educational attainment around middle-level qualifications. The third component is primarily characterized by a positive loading on high-school graduation and a large negative loading on some college education. It thus distinguishes counties in which educational attainment tends to stop at high school from counties in which residents are more likely to progress into post-secondary education.

Figure E1. Scree plot of principal-component eigenvalues

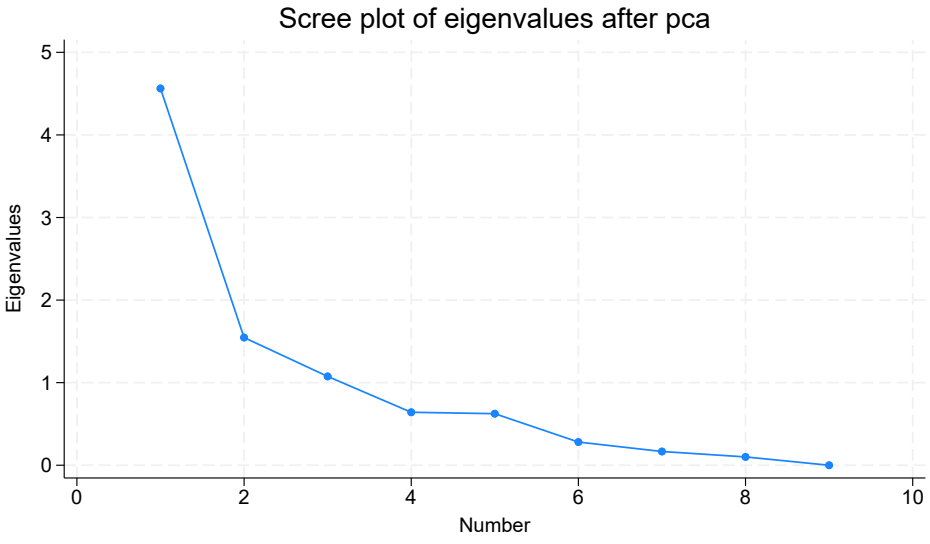


Table E1. Principal components analysis: First four components

Component	Eigenvalue	Proportion	Cumulative
Comp1	4.563	0.507	0.507
Comp2	1.547	0.172	0.679
Comp3	1.076	0.120	0.798
Comp4	0.642	0.071	0.870

Table E2. Principal components analysis: Loadings of the first three components

Variable	Comp1	Comp2	Comp3
Less than ninth grade	-0.294	-0.357	-0.160
Ninth to twelfth grade, no diploma	-0.406	-0.169	-0.078
High-school graduate	-0.299	0.350	0.559
Some college, no degree	0.112	0.418	-0.730
Associate's degree	0.217	0.493	0.003
Bachelor's degree	0.414	-0.279	-0.064
Graduate or professional degree	0.333	-0.465	0.013
Dividend income	0.403	0.025	0.277
Capital gains	0.395	0.096	0.203

Appendix F: Case study

To motivate our research, we sought anecdotal evidence on how the closure of large-bank branches, following a merger, may impact deposit pricing by local small banks. In June 2021, PNC Bank completed its acquisition of BBVA USA, becoming the fifth-largest bank in US. The merger involved integrating BBVA USA's network of over 600 branches into PNC's operations and led to branch closures, especially in areas with overlapping coverage. In the years following the merger, PNC announced a series of closures totaling approximately 450 branches across the US.[27]

One area affected by these closures was Birmingham in Jefferson County, Alabama. In 2023, we identified four former BBVA branches - now operated by PNC - that were closed: *Birmingham*, *The Grove*, *Avenue Drive Up* and *Daniel Building*, as listed in the relevant FDIC SoD dataset.[28] Notably, during the same period no small bank branches were closed in that area. Table F1 presents the number of branches of small banks located within a 3-mile radius of each closed branch, along with the corresponding deposit rate changes during the year of closure. For example, 13 branches of 10 small banks were located within 3 miles of the *Birmingham* branch, and these reported an average increase of 1.37% in their 6-month certificate of deposit rates for $10,000 deposits (6m10K). Moreover, Table F1 reports data for a control group of 34 branches of 18 small banks located more than 3 miles from any of the closed branches. This group reported an average increase of 0.85% in the same deposit product. Similarly, the average increase for 12m10K and 12m100K deposit rates is both 1.07% for nearby branches and 0.88% and 0.83% for faraway branches.

Table F1 also reports a univariate variance t-test of mean differences in deposit rate changes between the group of branches within the 3-mile radius and the control group. With the exception of *The Grove* branch, in all other cases, the mean differences for

[27] See https://www.pnc.com/content/dam/pnc-com/pdf/aboutpnc/CorporateResponsibilityReports/cra-public-file/List_of_PNC_Branch_Closings.pdf. While we cannot explicitly link each listed branch closure to the merger, the timing suggests that some of these closures were part of the branch network streamlining. In particular, former BBVA branch closures were more likely to be related to the merger.

[28] A fifth branch, *Parkway East*, was excluded from the analysis because there were no deposit rate data from nearby small banks.

6m10K rates are positive and statistically significant. Furthermore, tests for the 12-month certificates of deposit rates for $10,000 and $100,000 deposit amounts reveal similar patterns, albeit with weaker evidence. It is worth noting that *The Grove* branch - the only case without statistically significant results - also has the fewest nearby rival branches, indicating the lowest competition among the four cases. Overall, univariate analysis suggests that small banks may adjust deposit pricing in response to changes in local market structure, particularly after a dominant competitor exits. However, these findings remain illustrative and do not establish correlation, let alone causality.

Table F1. Small bank deposit rate changes after large bank branch closure

	Nearby small bank branches (<3 miles)					
Branch name	**No Branches**	**No Banks**	Stats	**Δ6m10K**	**Δ12m10K**	**Δ12m100K**
Birmingham	13	10	mean	1.37	1.07	1.07
			sd	1.71	1.58	1.58
			t-test	**3.19**	1.25	1.59
The Grove at 150	6	6	mean	0.48	0.61	0.62
			sd	0.57	0.69	0.70
			t-test	-2.02	-1.37	-1.07
2nd Avenue Drive Up	17	10	mean	1.33	1.11	1.11
			sd	1.80	1.74	1.74
			t-test	**3.41**	**1.73**	**2.11**
Daniel Building	19	12	mean	1.22	1.05	1.05
			sd	1.73	1.66	1.66
			t-test	**2.89**	1.40	**1.82**
	Distanced small bank branches (>3 miles)					
Branch name	**No of Branches**	**No of Banks**	Stats	**Δ6m10K**	**Δ12m10K**	**Δ12m100K**
Control	34	18	mean	0.85	0.88	0.83
			sd	1.34	1.32	1.30

To provide more information regarding the selected small bank branches that were located nearby the closed former BBVA branches as well as the control group of small bank branches that were located further away from the closed branches, we prepare a map of the branches of small banks located within a 3-mile radius of each closed branch separately. These maps were produced using geospatial visualization tools in Python. Geographic coordinates for each branch (latitude and longitude) were combined with open-source map tiles to plot the locations of closed PNC branches and competitor institutions. Different marker colors were used to distinguish closed former BBVA branches from competitor

branches of small banks with assets less than 100 billion. Furthermore, distances are computed using the great-circle distance on the WGS-84 ellipsoid (the standard Earth model used for GPS). That means the distances are straight-line geodesic distances, not road network or driving distances. The resulting maps provide an intuitive representation of branch proximity and spatial clustering, complementing the statistical analysis.

Figure F1 is a map of the 19 nearby branches of small banks located within a 3-mile radius of the *Daniel Building* branch during the year of closure. Similarly, Figure F2 is a map of the 13 nearby branches of small banks located within a 3-mile radius of the *Birmingham* branch. Figure F3 is a map of the 17 nearby branches of small banks located within a 3-mile radius of the *Avenue Drive Up* branch. Figure F4 is a map of the 6 nearby branches of small banks located within a 3-mile radius of *The Grove* branch, showing a more sparsely populated local bank market. Finally, Figure F5 is a map of the 34 small bank branches located in the same county that are collectively more than 3 miles away from all four former BBVA closed branches.

The mechanism described by our model is that branch closures generate attention among households, prompting them to search for better deposit returns. To examine this mechanism in our case study, we downloaded Google Trends data designed to capture changes over time in public interest in bank deposit pricing. We constructed the Trends series using a set of closely related search terms that reflect common ways consumers seek information about deposit interest rates and savings returns. These terms include general phrasing, product-specific language, and comparison-oriented queries used when shopping across banks. We also include directional questions about rate movements and a general informational query. These queries are combined into a single Google Trends measure intended to summarize overall consumer search activity related to deposit rates. The resulting series is a normalized index compiled at the Core-Based Statistical Area (CBSA) level based on the IP address of search users.

Figure F6 (top panel) plots the Trends series for the Birmingham–Cullman–Talladega, AL CBSA, which includes our focal area of Birmingham (Jefferson County). The figure shows a clear increase in search intensity beginning in 2021 and continuing through 2023.

We then repeat the same procedure for the set of CBSAs that include counties with the strongest social ties to the focal area (the six counties with the highest SCI) and, separately, for CBSAs that include counties with the weakest ties (the six counties with the lowest SCI), which are also geographically distant (more than 50 miles) from Birmingham, AL. Figure F6 (bottom panel) reports the arithmetic average of the Google Trends series within each group. Areas with strong social ties display a rising pattern over 2021–2023, whereas areas with weak ties exhibit a comparatively flat trend for the same period. While this descriptive evidence may also be related to concurrent trends other than the branch closures, it is consistent with the mechanism that branch closures coincide with heightened household attention to deposit pricing, and that this attention may be transmitted through social networks to geographically distant but socially connected areas.

Figure F1. ***Daniel Building*** **(former BBVA closed) branch and its nearby small bank branches.**

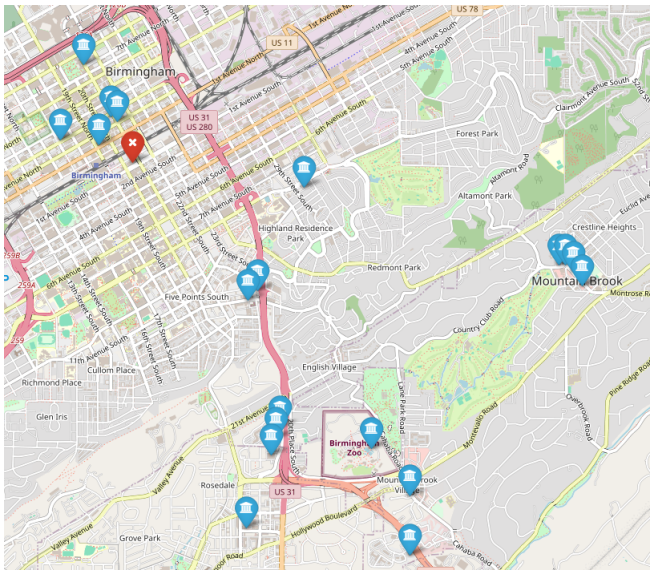


Figure F2. ***Birmingham*** **(former BBVA closed) branch and its nearby small bank branches.**

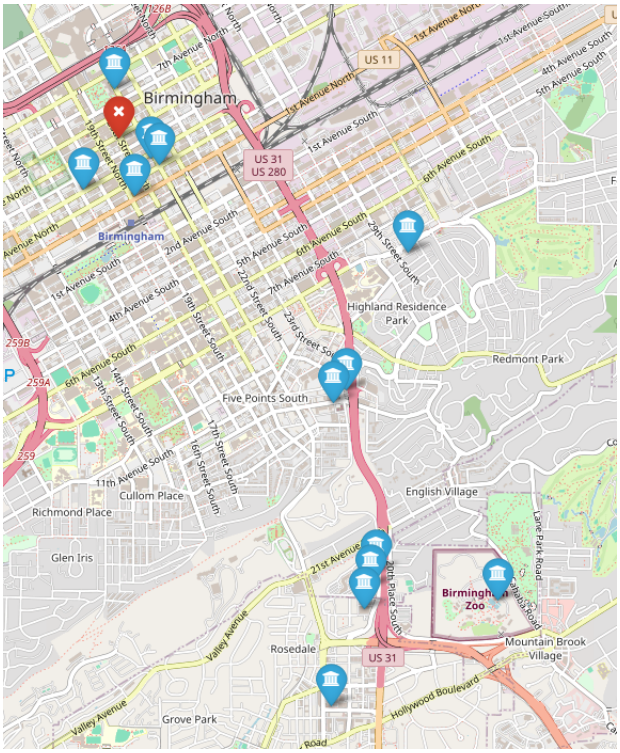


Figure F3. ***Avenue Drive Up*** **(former BBVA closed) branch and its nearby small bank branches.**

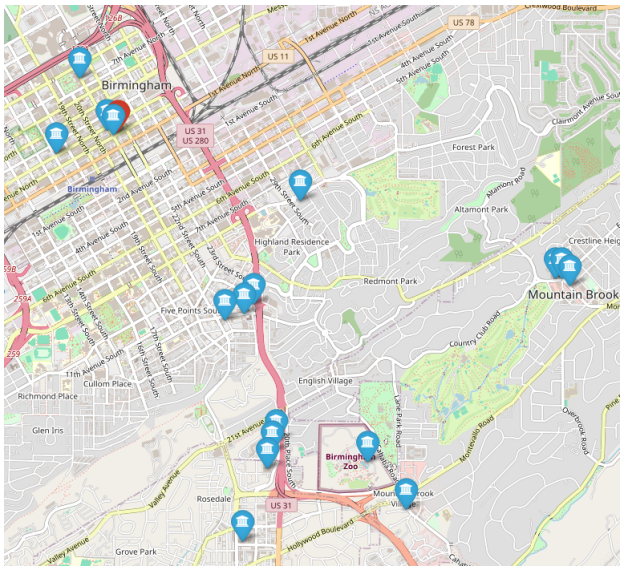


Figure F4. ***The Grove*** **(former BBVA closed) branch and its nearby small bank branches.**

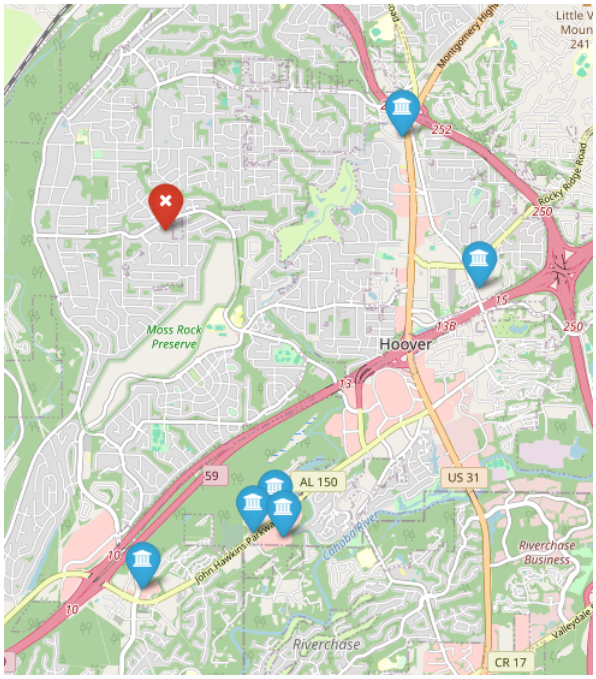


Figure F5. ***The Control*** **group of small bank branches from the same region that are further away from all four former BBVA closed branches.**

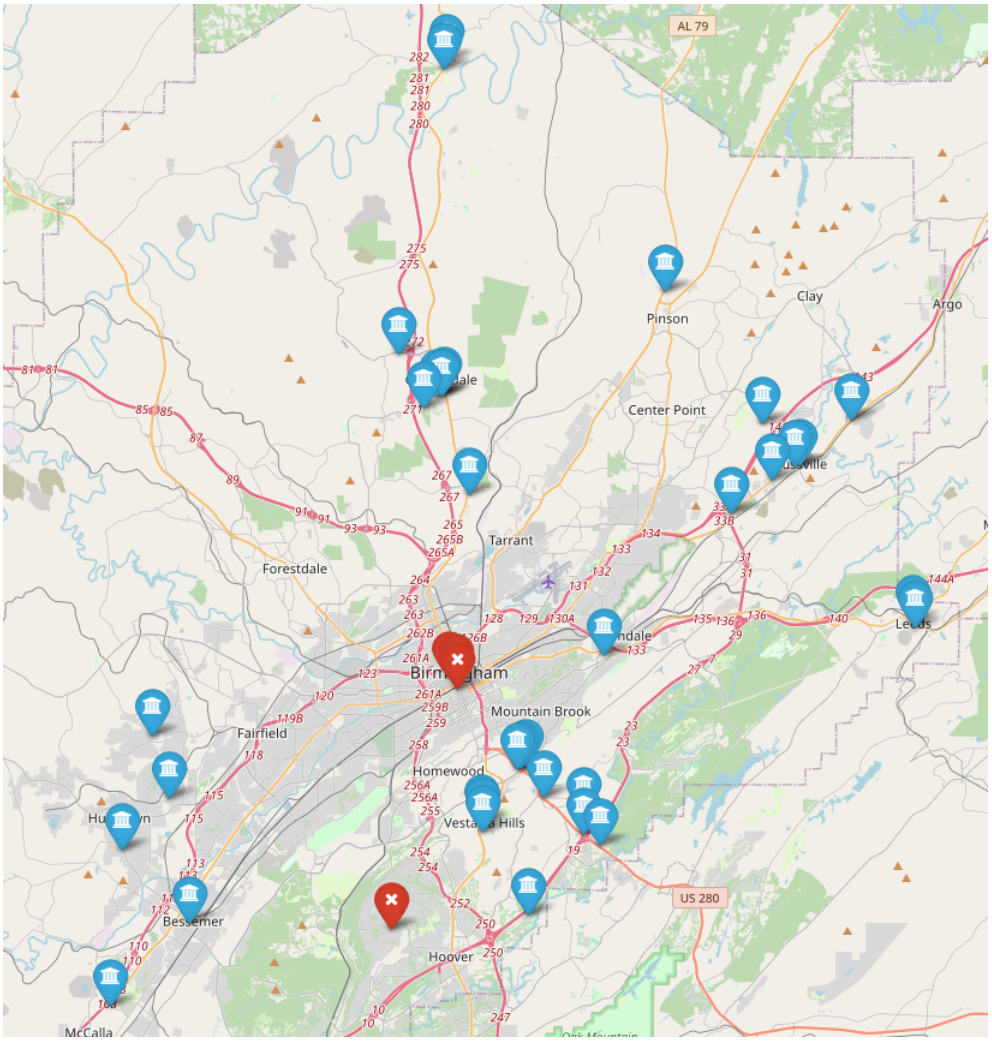


Figure F6. Google trend data searches for deposit rates

