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Do banks respond to their friends' markets? Social spillovers in deposit pricing

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Abstract

We study how deposit rate shocks transmit across banking markets through digital social ties. Depositors' inattention implies that households react to outside rate changes only when social networks make these changes salient, inducing connected banks to raise their own rates. Using merger-driven shocks to local deposit rates and county-level social connectedness, we show that small banks increase rates in response to shocks occurring in socially linked but geographically distant counties. Spillovers are economically meaningful, persistent, and stronger in competitive markets and in counties with more financially sophisticated households. Digital social ties therefore activate depositor search and integrate deposit markets across space.

Keywords: Social connections, deposit pricing, information transmission, limited attention, uniform pricing
JEL classification: G20; G21; G23; G29

Non-technical summary

Deposit markets are typically viewed as local and segmented. It stands to reason that banks' pricing decisions are affected by consumer interactions, now increasingly mediated through digital social networks. When peer influence is strong, local market concentration changes may have amplified effects on deposit rates, transmitted through social ties. Thus, our identification strategy enables causal estimates of the spillover of deposit price changes across US county-level social networks.

This study examines whether information transmitted through online social networks alters deposit pricing across markets. To formalize the mechanism driving social spillovers in deposit pricing, we develop a stylized model of deposit rate competition across socially connected counties. Social ties can make financial opportunities salient to inattentive households, and in this setting they expose depositors to rate changes occurring elsewhere, triggering search for better offers. This search response increases deposit-market elasticity and induces small banks to adjust prices even in markets with no geographic connection to the original shock. The model incorporates behavioral frictions such as inattention and heterogeneous search costs, and predicts that social connectedness, financial sophistication, and market competitiveness jointly amplify deposit rate responses.

We test these predictions empirically by examining how small banks in one county respond to competitive shocks occurring in socially connected - but geographically distinct - counties. Using merger-driven variation in deposit rates and measures of digital social connectedness, this study shows that small banks raise rates in socially linked markets. The validity of this approach hinges on the exogeneity of the shocks, a condition met in our setting given the localized and idiosyncratic nature of large bank exits in socially connected counties. To further support our hypothesis that social networks facilitate the exchange of deposit-related information between bank customers, we conduct a series of robustness checks to rule out alternative mechanisms.

Our empirical analysis does not allow to distinguish between all possible explanations why social connections might influence deposit pricing decisions of banks. However, it enables us to test the prediction that customers with higher levels of financial sophistication are more more equipped to search for higher deposit rates. Using a new financial sophistication measure we find that social spillovers in deposit pricing are more pronounced in high-sophistication counties.

A corollary of our findings is that increased participation in online social networks fosters lower variation in deposit rates among small banks across geographically distant but socially proximate markets. Specifically, as social interactions intensify, they reduce local market heterogeneity by facilitating the transmission of financial information, prompting small banks to adjust toward a common equilibrium rate. Crucially, we find that social connectivity accelerates the rate of this type of convergence, but this effect is exclusive to small banks. This result underscores the role of social networks in harmonizing pricing behaviour among smaller banks, which are more sensitive to peer influence and local competitive dynamics than their larger counterparts.

1 Introduction

Deposit markets are typically viewed as local and segmented. Consumer inertia and limited attention allow small banks to exercise pricing power within their immediate markets (Calem & Nakamura 1998, Drechsler, Savov & Schnabl 2017). In contrast, recent work shows that large banks often rely on uniform pricing that largely ignores local competitive conditions (Begenau & Stafford 2023, d'Avernas, Eisfeldt, Huang, Stanton & Wallace 2023). At the same time, households increasingly obtain financial information through digital social interactions that extend well beyond their immediate environment, potentially weakening traditional geographic boundaries and exposing consumers to interest-rate developments elsewhere (Kuchler, Li, Peng, Stroebel & Zhou 2022, Cookson, Mullins & Niessner 2024). Whether such social ties meaningfully influence deposit competition remains an open question.

We examine whether information transmitted through online social networks alters deposit pricing across markets. Social ties can make financial opportunities salient to inattentive households[1], and in our setting they expose depositors to rate changes occurring elsewhere, triggering search for better offers. This search response increases deposit-market elasticity and induces small banks to adjust prices even in markets with no geographic connection to the original shock. Using merger-driven variation in deposit rates and measures of digital social connectedness, we show that small banks raise rates in socially linked markets. These spillovers are economically meaningful, persistent, and strongest in more competitive and financially sophisticated markets.

To formalize the mechanism driving social spillovers in deposit pricing, we develop a stylized model of deposit rate competition across socially connected counties. In the model, a deposit rate shift in county A generates social-media buzz, which spreads to county B via the intensity of social connectedness. This buzz raises awareness among depositors in

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

county B, prompting them to search for better rates if the expected benefit exceeds their search cost. The share of active searchers increases with awareness, financial sophistication and local competition, making deposits more contestable and intensifying rate competition among banks. Small banks in county B, which compete à la Bertrand with differentiated products, respond by raising deposit rates. The model incorporates behavioral frictions such as inattention and heterogeneous search costs, and predicts that social connectedness, financial sophistication, and market competitiveness jointly amplify deposit rate responses.

We test these predictions empirically by examining how small banks in one county respond to competitive shocks occurring in socially connected - but geographically distinct - counties. Our identification strategy leverages quasi-experimental variation in market structure, drawing on recent applications of shift-share designs (e.g., Bartik instruments in labor and housing markets). The validity of this approach hinges on the exogeneity of the shocks, a condition met in our setting given the localized and idiosyncratic nature of merger-driven large bank exits in socially connected counties. It stands to reason that banks' pricing decisions are affected by consumer interactions, now increasingly mediated through digital social networks. When peer influence is strong, local market concentration changes may have amplified effects on deposit rates, transmitted through social ties. Thus, our identification strategy enables causal estimates of the spillover of deposit price changes across US county-level social networks.

We begin by documenting empirically how small banks adjust their deposit rates in response to the loss of deposits of a large bank, which represents the pool of "potential" customers for the small regional banks. For this, we use an instrumental-variables strategy estimated via two-stage least squares (2SLS). In the first stage, we instrument the decline in large-bank deposits with an indicator for large-bank branch closures in a county. To ensure exogenous variation, we focus on closures by large banks involved in a merger within a two-year window, which the literature documents as unconfounded with local market characteristics (Garmaise & Moskowitz 2006). In the second step, we estimate separately the impact of these market share changes on deposit rates offered by large and small banks. Our findings offer new insights about the heterogeneity in deposit pricing behaviour: only small banks exhibit a positive and significant increase in rates while large bank rates show no change. This supports our hypothesis that small banks are more sensitive to local market competition dynamics, while large banks adhere to uniform pricing strategies. Moreover, the effect is most pronounced in markets where competition between small banks is high, consistent with the prediction that small banks compete on price.

We then exploit this variation introduced by large bank exits to examine whether deposit rate changes in one market spillover to socially connected "peer" areas. To measure these relationships, we use the Social Connectedness Index (SCI) developed by Bailey, Cao, Kuchler & Stroebel (2018), which captures the intensity of Facebook friendship links between US 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). Our use of the SCI builds on recent evidence that SCI captures economically meaningful peer effects in financial decisions (Hu 2022). We combine this measure with branch-level deposit rate data from RateWatch and information on the quantity of deposits at the branch level from the FDIC's Summary of Deposits (SOD) dataset to construct two key variables: *Social Deposit Rate* (SDR) - which captures one county's indirect exposure to deposit rate changes through social connections with all other counties - and *Social Large-bank Branch Closure* (SLBC) - which captures the indirect exposure of banks in one county to large bank market share changes in socially connected areas.

The causal inference faces one major challenge arising from the existence of unobserved common factors that drive deposit rates to change simultaneously across multiple markets without network spillovers. To isolate the role of social networks, we again employ a two-stage least square approach. In the first step, we instrument for social proximity to deposit rate changes using the large banks' branch closures across all socially connected areas. This builds on our earlier finding that small banks compete on deposit prices in response to large bank market share losses caused by branch closures. In the second step, we estimate the impact of these socially connected rate changes on deposit rates of banks in the focal area. To further address endogeneity concerns, we include county and year fixed effects, control for time-varying characteristics of the focal area, and include a distance-weighted measure of exposure to account for geographic proximity. Our results support the hypothesis that deposit rates of small banks in a focal area increase after rate increases in socially connected counties. The social spillover effect is strongest in markets with high small bank competition.

To further support our hypothesis that social networks facilitate the exchange of deposit-related information between bank customers, we conduct a series of robustness checks to rule out alternative mechanisms. First, we exclude counties within 25- and 50-mile radii of the focal county to rule out spatial proximity effects. Moreover, we confirm that results are not driven by cross-country economic linkages (Flynn & Wang 2025). We refine our exposure measure by conditioning on counties with high penetration of residential broadband internet to ensure that social connections reflect "active" online engagement that facilitates information exchange. Finally, we draw from recent literature that links financial sophistication to the market power of banks (Drechsler et al. 2017, Fleckenstein & Longstaff 2024), and from literature that links financial sophistication to the digital sophistication of individuals (Gambacorta, Gambacorta & Mihet 2023). We expect that customers with higher levels of financial sophistication are more active in deposit-related information exchange using social networks. At the same time, we expect that small banks operating in more financially sophisticated counties are more responsive to peer-driven deposit rate changes. To test this, we construct a financial sophistication measure using Principal Component Analysis (PCA) on nine correlated county-level variables capturing educational attainment and stock market participation. We find that social spillovers in deposit pricing are more pronounced in high-sophistication counties, suggesting that informed consumers amplify the transmission of deposit rate changes through social networks.

A corollary of our findings is that increased participation in online social networks fosters lower variation in deposit rates among small banks across geographically distant but socially proximate markets. Specifically, as social interactions intensify, they reduce local market heterogeneity by facilitating the transmission of financial information, prompting small banks to adjust toward a common equilibrium rate. To formally test this convergence dynamic, we employ a β-convergence framework (Barro & Sala-i Martin 1992), examining whether initial disparities between a county's deposit rates and the weighted average rates of its socially connected peers diminish as the use of social networks increases. Our empirical strategy relies on a Differences-in-Differences specification, where a negative and statistically significant β coefficient provides evidence of convergence in deposit rates across counties and banks. Crucially, we find that social connectivity accelerates the rate of convergence, but this effect is exclusive to small banks. This result underscores the role of social networks in harmonizing pricing behaviour among smaller banks, which are more sensitive to peer influence and local competitive dynamics than their larger counterparts.

Relation to the literature. This paper provides, to the best of our knowledge, the first empirical evidence that social networks impact bank deposit rates through changes in local market concentration. Our analysis contributes to three distinct strands of literature. First, we extend the literature on uniform deposit pricing of banks. 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 offering new evidence on the differential responsiveness of small versus large banks to exogenous shocks in local market concentration.

Second, our paper contributes to the growing literature on 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 and insurance take-up decisions (Hu 2022). The paper closest to our work is Kuchler et al. (2022), who examine 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.

Finally, this paper adds 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 deposits, suggesting that social ties transmit economic shocks. Rehbein & Rother (2025) show that cross-county bank lending intensifies with greater social connectedness, while Zhou (2025) examine 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.

The remainder of the paper is structured as follows. In Section 2, we describe the model. In Section 3, we describe the data and the construction of key variables. In Section 4, we outline the empirical strategy and present results on the differential deposit pricing behaviour of small versus large banks following changes in local market concentration. In Section 4, we examine the spillover effects of deposit rate changes across socially connected counties. In

Section 5, we investigate the role of online social connectedness in accelerating convergence toward a common deposit rate among small banks. In Section 6, we conclude.

2 Mechanism

This section provides a simple framework that describes how a deposit rate shock in one local market can affect deposit pricing in another socially-connected 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. Local market A experiences an exogenous increase in local deposit rates of size Δr_A, for example following 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 residents of A and B, and α captures the overall visibility of financial content on the platform. Depositors in 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 remain inattentive and do not initiate any search.

Once aware, depositors decide whether to search for better deposit rates. A share λ of households is financially sophisticated and faces a low search cost c_L, while unsophisticated households face a higher cost $c_H > c_L$. However, both types may search when awareness is sufficiently strong. The endogenous share of active searchers $m = m(p, \lambda)$ increases in both awareness and sophistication. Active searchers observe and compare all offers and become sensitive to differences in rates, making local deposits more contestable.

Banks in local market B compete a la Bertrand in differentiated products. Each bank i faces deposit demand

$$D_i = a - br_i + d\bar{r}_{-i} + \eta m,$$

where $\bar{r}_{-i}$ is the average rate of competitors, b captures own-rate sensitivity, d represents substitution toward competitors' rates, and ηm captures how search increases the size of the contestable depositor pool. Banks set deposit rates to maximize their return $(R - r_i)D_i$. The equilibrium deposit rate is

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

Thus, deposit rates in B respond to shocks in A due to the rise in social-media-driven awareness and the resulting increase in depositor's search activity.

The sequence of events in the model is summarized in the Figure 1.

$t = 0$	$t = 1$	$t = 2$
• 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: $m = m(p, \lambda)$	• Banks set deposit rates r_B^*

Figure 1. The timeline.

This mechanism yields two empirical predictions. First, social networks transmit deposit-market conditions across geographic boundaries: local markets more connected to A experience larger spillovers. Second, the magnitude of the spillover depends on local household characteristics: local markets with more financially sophisticated households 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 exhibit larger increases in local deposit rates.* Intuitively, social connections increase exposure to deposit-related content, raising awareness and expanding the contestable depositor base.

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, increasing deposit elasticity, 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 strength of its social connections to local market B, and (iii) the financial sophistication of households in B. We proceed by showing how we map these objects into the data.

3 Data and social connectedness

We compile bank and economic data at the county - our definition of local market - and national levels from several sources. Our dataset consists of all US commercial and savings and loan banks that report data over the period 2011 to 2023.[2] 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 and so it would be impossible to attribute deposits of online banks to any geographically specific or socially connected area.

This section describes the main datasets used and the measurement of social network spillovers at the county level. Table A1 and Table A3 in the Appendix B report summary statistics for the deposit rates and for the main control variables in the form (time-differences) used in the empirical analysis. Table A4 in the Appendix B gives the definition of the variables.

3.1 Branch-level bank data

Our main dataset consists of branch-level deposit rates from RateWatch, which surveys over 100,000 bank branches weekly to collect advertised deposit rates and annual percentage

[2] The empirical investigation uses time differences of variables, thus the effective period starts from 2012.

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. We include both "rate setter" branches and "follower" branches, whose deposit rates are determined by a centralized rate-setting policy. Our choice to include all branches is backed by the fact that excluding followers would eliminate over 90% of US commercial bank branches (Begenau & Stafford 2023). Furthermore, including "follower" branches, many of them being branches of large banks, aligns with our theoretical argument, which posits that large banks tend to use uniform price setting, making local competition more relevant for small banks.

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 (*12MCD10K*). To test the robustness of our findings across different types, maturities and sizes, we also report results from three additional deposit products: the 6-month CD with a $10,000 minimum account size (*6MCD10K*), the 12-month CD with a $100,000 minimum account size (*12MCD100K*), and money market accounts (MMs) with a $10,000 minimum account size (*mm10k*). 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.[3] 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

[3] 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 $t + 1$.

exceeds $100 billion, following the FED's definition of large banking organizations.[4] We use these data to compute the Herfindahl-Hirschman index for small banks within a county-level deposit market, denoted as (*SBHHI*), 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 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:

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

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.[5] 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).

The index has been widely adopted in empirical work on housing markets (Bailey, Cao, Kuchler & Stroebel 2018), trade (Bailey, Gupta, Hillenbrand, Kuchler, Richmond & Stroebel 2021), product adoption (Bailey et al. 2022), and bank lending (Rehbein & Rother 2025). Our use of SCI follows a growing literature showing that SCI captures economically mean-

[4] https://www.federalreserve.gov/supervisionreg/topics/large-banking-organization-supervision.htm

[5] 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.

ingful peer effects in financial decision-making, including mortgage leverage and related housing-finance choices (Bailey, Cao, Kuchler & Stroebel 2018, Bailey et al. 2019), investor portfolio and trading behavior among both retail and institutional investors (Bali, Hirshleifer, Peng, Tang & Wang 2021, Kuchler et al. 2022), online credit supply and demand (Allen, Peng & Shan 2020), and insurance demand (Hu 2022). In particular, Hu (2022) shows that households increase flood-insurance purchases when their socially connected, but geographically remote, friends experience flooding events or targeted insurance campaigns. Because these shocks do not alter local fundamentals, the behavioral response can only operate through social networks, helping overcome classic challenges in peer-effects identification such as endogenous network formation, correlated shocks, and reflection.

This evidence supports our empirical strategy: shocks to deposit-market structure in socially connected counties provide quasi-experimental variation that is orthogonal to local conditions, allowing us to isolate the causal impact of social spillovers in deposit pricing. Moreover, the finding by Hu (2022) that social interactions measured by SCI primarily trigger attention and salience rather than transmitting technical information aligns closely with our mechanism, in which depositors become aware of rate changes elsewhere through social ties.

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, excluding Alaska and Connecticut.[6] County-level population data are sourced from the Surveillance, Epidemiology, and End Results (SEER) Program.[7] We control for the total population of each county (*Population*). Moreover, demographic variation in savings behavior affects local deposit markets (Becker 2007), so we include the proportion of the population above 65 years old (*Seniors*) as a

[6] Over our sample period, Alaska experienced frequent redraws of local "boroughs" - the geographical equivalent to a county - making 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.

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

control. 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. Geographic proximity between counties is measured using the NBER County Distance Database and the Haversine formula based on internal points in the geographic area.

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 24 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 the Online Appendix.

4 Local market competition and deposit rates

This section provides empirical motivation for the differential deposit pricing behaviour observed between large and small banks. A growing literature documents that banks tend to engage in uniform rate setting. For example, d'Avernas et al. (2023) find that customers of large banks receive lower deposit rates on average and exhibit lower rate-sensitivity. This is attributed to their higher willingness to pay for superior liquidity services - such as extensive branch and ATM networks, tailored online banking, and a broad array of financial services - offered by large banks. Thus, large banks offer lower rates across markets, reflecting the lower average elasticity of depositors they serve. On the other hand, small banks typically offer higher deposit rates to attract customers, compensating for limited liquidity services. In essence, large banks compete on service quality, while small banks compete on price.

4.1 Empirical specification

Assume a county j at time t, where several local single-market small banks operate offering deposit rates r_j while a large multi-market bank with branches in this county offers uniform deposit prices r. If the large bank closes its branch(es) in that county, the local competitive landscape changes. How do small banks respond to this change? To attract the unserved customers of the closed branch(es), small banks may respond by competing on price - raising their deposit rates. For example, this dynamic was observed following PNC Bank's acquisition of BBVA USA, where branch closures in Birmingham, Alabama provided a natural experiment.[8]

To test formally this hypothesis, we use a two-stage least squares (2SLS) regression where in the first step the large bank branch closure serves as an exogenous variable for

[8] Deposit rates at nearby small-bank branches increased more than those further away, suggesting pricing adjustments in response to reduced competition. Full details and statistical analysis are presented in the case study in the Appendix C.

the change in large banks' market share.[9] The exclusion restriction assumes that branch closures affect small bank rates only through the associated loss of the large bank's market share. 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. Merger-induced closures of large bank branches 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). Thus, the first stage regression is:

$$\Delta LBMS_{j,t} = \alpha + \alpha_1 LBC_{j,t} + \alpha_2 \Delta x_{j,t} + f_j + f_t + \eta_{j,t} \tag{2}$$

where $\Delta LBMS_{j,t}$ is the loss of market share of large banks in county j following the closure of a large bank branch, $LBC_{j,t}$ is a dummy that equals one if there is a merger-induced large-bank branch closure. Then, the second stage regression is:

$$\Delta r_{j,t} = \beta + \beta_1 \Delta \widehat{LBM}S_{j,t} + \beta_2 \Delta x_{j,t} + f_j + f_t + \epsilon_{j,t} \tag{3}$$

where $\Delta r_{j,t}$ is the variable of interest, *i.e.*, the change in rates of deposits of different sizes and maturities. Moreover, the set of control variables $\Delta x_{j,t}$ includes the changes in small banks' market concentration HHI (*SBHHI*), that captures if all small banks attract equally deposits (in which case the ratio remains similar) or if deposits flow to a handful of small banks. Other control variables include changes in demographic factors known for their influence on deposits such as the percentage of senior population (*Seniors*), total population (*Population*), real GDP per capita (*Realgdppc*) and financial sophistication level (*FSophistication*) in the county. We also include county and time fixed effects, f_j and f_t, ensuring that identification comes from within-unit deviation in rates $\Delta r_{j,t}$ from pre- and post- branch closure trends.

[9] The closure of a branch with few deposits will not have the same impact on deposit rates as the closure of a branch with a large deposit base. In the latter case, small banks will compete more intensely, bidding their deposit rates higher to attract more new customers.

Finally, $\epsilon_{j,t}$ is the error term adjusted for within-county correlation and for the variability introduced by the first-stage estimation.

We anticipate that local competition conditions play a role and specifically that low market concentration of small banks in the county will amplify the effect, leading to small banks offering higher deposit rates after the branch closure of the large bank. To test this, we interact the variable $\Delta LBMS$ in eq.(3) with the dummy *HighComp* which equals one when the county's time-median HHI index of the small banks is lower than 1,800.[10] In the first stage, the interaction of ΔLBC with *HighComp* serves as the instrument for the interaction of $\Delta LBMS$ with *HighComp*.

4.2 Panel regression estimates

Deposit rate data is available at a quarterly frequency, whereas $LBMS$ is observed annually. Consequently, we define the year as our time variable and calculate differences based on year-end values. Our final sample is a county-year panel spanning from 2012 through 2023. To avoid confounding effects, we exclude country-year observations with small bank branch closures taking place in the same year with large bank branch closures.

Table 1 and Table 2 present the second stage regression results using eq.(3) for the effect of changes in local bank concentration, after a large bank branch closes, on deposit rates for small and large banks, respectively.[11]

[Insert Table 1 and Table 2, here]

We find support for our first hypothesis: small banks increase their deposit rates following a large bank's decision to close a branch in the same county. As shown in columns (1)-(4) in Table 1, the estimated coefficient for the (*12MCD10K*) is 0.822 which implies that a one standard deviation decrease in large bank market share (sd=0.033) driven by the branch closure leads to a 2.71 basis points increase in the rate. The effect is lower in magnitude, but

[10] According to the guidelines referred to mergers by the Department of Justice, when HHI is above 1,800 markets are characterised as "highly concentrated".

[11] First stage regression results are reported in Table C4 column (1) in the Online Appendix.

still significant, for the *mm10k* consistent with the generally lower rates in money market accounts than those in certificates of deposits. Columns (5)-(8) provide further evidence for the competition channel. In counties with high local competition among small banks, the impact of large bank branch closure is amplified. The interaction coefficient of 2.502 for the (*12MCD10K*) suggests that a one standard deviation loss in large bank market share (sd=0.033) results in a 8.26 basis points increase in deposit rates in highly competitive markets. On the other hand, when local competition between small banks is low, the effect is negligible and statistically insignificant. Finally, Table 2 confirms that large banks, in general, do not adjust their deposit rates in response to local market concentration changes, consistent with the expectation that large banks offer uniform deposit pricing across different regions.

5 Social connectedness and deposit rates

In this section, we turn to our main research hypothesis H1-H2. The empirical estimates from the previous section inform our identification strategy for testing social network effects in deposit markets. To illustrate, consider an expanded version of the previous example. Suppose another county, c, is geographically distant but socially connected to the county j where, as stated earlier, the large-bank branch closure increased price competition among small banks. *Hypothesis 1* is equivalent to testing whether small banks in the focal county c adjust their deposit pricing in response to changes in deposit pricing in county j due to their strong social ties.

5.1 Measuring social network spillovers

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 in banks in other counties. 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:

$$SDR_{c,t} = \sum_{j \in C-c} SCI^*_{c,j} \times \Delta r_{j,t} \tag{4}$$

where $SCI^*_{c,j}$ is the SCI between counties c and j, standardized for interpretation reasons by the total number of connections (in thousands) within US, and $\Delta r_{j,t}$ is the change in deposit rates in county j at time t. We take the sum over all counties $C - c$ except the focal county c. The network spillover variable assigns greater weight to counties that are more socially connected to county c. A high $SCI^*_{c,j}$ implies that financial 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.

Furthermore, we introduce a second variable, *Social Large-bank Branch Closure* ($SLBC$), which captures the indirect exposure of banks in county c to large bank market share changes in socially connected areas at time t. This variable is defined as:

$$SLBC_{c,t} = \sum_{j \in C-c} SCI^*_{c,j} \times LBC_{j,t} \tag{5}$$

where $LBC_{j,t}$ is an indicator variable capturing large bank branch closures in county j at time t. The underlying premise is that such closures may instrument the deposit behaviour and pricing strategies in socially connected counties.

Social connectedness tends to be positively correlated with geographic proximity, as well as with economic and cultural factors (Bailey, Cao, Kuchler, Stroebel & Wong 2018). However, substantial variation in social ties remains unexplained by these factors. In our empirical specification, we include an alternative exposure measure analogous to eq.(4), but with weights based on geographic proximity. Specifically, the *Distant Deposit Rate* (DDR) is defined as:

$$DDR_{c,t} = \sum_{j \in C-c} Dist_{c,j} \times \Delta r_{j,t}$$

where $Dist_{c,j}$ is the inverse physical distance between counties c and j. 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.

5.2 Empirical specification

To examine whether deposit rates in a focal county c are affected by rate changes in socially connected counties, we employ a two-stage least squares (2SLS) regression setup using the measures of social proximity defined in (4) and (5). First, we estimate the following regression:

$$SDR_{c,t} = \beta + \beta_1 SLBC_{c,t} + \beta_2 \Delta x_{c,t} + f_c + f_t + \epsilon_{c,t} \tag{6}$$

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

$$\Delta r_{c,t} = \gamma + \gamma_1 \widehat{SDR}_{c,t} + \gamma_2 \Delta x_{c,t} + f_c + f_t + \epsilon_{c,t} \tag{7}$$

The key parameter of interest is γ_1 capturing the social spillover effect on deposit rate changes. We include the same control set of variables as in eq.(3) and add the geographic proximity between counties using the *Distant Deposit Rate* (*DDR*) measure. Finally, f_c and f_t are county and time fixed effects, and $\epsilon_{c,t}$ is the error term adjusted for within-county correlation.

Our identification strategy hidges on the exogeneity of the variable *Social Deposit Rate*, which captures the extent to which county c is exposed through social ties to rate changes that occur in other counties. Thus, the *Social Deposit Rate* assigns greater weight to deposit rate changes in counties that are more socially connected, thereby amplifying the influence of shocks in these regions.

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 eq. (5). 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. This is supported by the fact that most socially connected counties are geographically and administratively distinct, making unlikely that merger-induced branch closures of large banks in peer counties are influenced by market conditions in the focal county. Moreover, we 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. Finally, empirical evidence presented in Section 4 confirms that the instrument *SLBC* is strongly correlated with *SDR*, satisfying the relevance condition.

Taken together, by leveraging exogenous variation in deposit rate changes from socially connected counties via the *shift-share* instrument and controlling for both county and time fixed effects, our empirical strategy isolates within-county variation in deposit rate changes ($\Delta r_{c,t}$), caused by the heterogeneous exposure to exogenous deposit rate changes of socially connected areas. This approach provides robust evidence for the causal influence of social spillovers in deposit pricing advancing the understanding of how non-economic linkages shape financial outcomes across regions.

5.3 Panel regression estimates

In this part of the analysis, we restrict the sample period to 2016-2023, during which the total number of Facebook users across all US counties exceeded 70% of total US population.[12]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.

To mitigate potential confounding effects, we exclude county-year observations where either small or large bank branch closures occurred. In this way, we ensure that observed deposit rate changes in the focal area are not driven by local shifts in market structure.

Table 3 shows the second-stage estimates from eq.(7) while the first stage regression results are reported in Table C4 columns (2)-(5) in the Online Appendix. In all specifications in Table 3, we find a strong, positive and statistically significant relationship suggesting that small banks in a focal county increase their deposit rates when small banks in socially connected counties raise theirs in response to local competition changes. Specifically, the estimated coefficient for the (*12MCD10K*) is 1.34, implying that a one standard deviation increase in deposit rates in socially connected counties (sd=0.174) leads to a 23.3 basis points increase in the focal county's rate.

[Insert Table 3, here]

All in all, consistent with Hypothesis 1, we find that small banks increase deposit rates in response to shocks occurring in socially connected but geographically distant counties. This confirms that social ties transmit deposit-market conditions across geographic boundaries. Importantly, these results remain robust after controlling for geographic proximity using the *DDR* measure. While the variable itself is positive, confirming that nearby counties exert competitive pressures, it is not always statistically significant. This suggests that our measure of social proximity of deposit rates captures social spillover effects that are distinct from physical proximity between counties. Also, we find that higher GDP per capita change is associated with higher deposit rate changes offered by small banks.

[12] 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.

Furthermore, we expect that this social network spillover effect is amplified in counties with a more competitive environment among small banks. This expectation aligns with the idea that banks enjoy greater market power when there are fewer small banks competing locally. Columns (5)-(8) of Table 3 provide empirical support for this relationship. The positive and statistically significant coefficient on the interaction term confirms that the spillover effect is stronger in highly competitive markets. In these settings, small banks are more responsive to deposit rate changes originating in socially connected counties.

5.4 The role of customers' financial sophistication

Recent research highlights that customers' lack of financial sophistication is a key source of banks' market power in deposit rate setting. Drechsler et al. (2017) show that proxies for financial sophistication such as age, income, and education significantly influence banks' pricing power and that deposit rates tend to be less sensitive to rate changes in areas with lower levels of financial sophistication. Fleckenstein & Longstaff (2024) further argue that financially unsophisticated customers often invest in - or automatically roll over into - tenors with dominated rates, unaware of better alternatives. In contrast, financially sophisticated customers are more likely to reject suboptimal rates, limiting banks' ability to benefit from offering dominated rates. At the same time, financial sophistication is positively associated with digital engagement, which facilitates the use of social networks. For example, (Gambacorta et al. 2023) show that digital literacy enhances access to financial technology, which in turn improves financial portfolio choices. Following this literature, we run direct empirical tests for our model's *Hypothesis 2* that the social spillover effect is stronger in local markets with more financially sophisticated households.

Using our composite measure of financial sophistication, we classify counties into high and low financial sophistication markets based on the sample median. We then assess the interplay between customer financial sophistication, and social connected deposit rates using the interaction effect. The results in columns (1)-(4) of Table 4 show that small banks are more likely to raise deposit rates in response to exogenous rate changes in socially connected counties when operating in markets with a large base of financially sophisticated customers. In line with Hypothesis 2, the spillover effect is significantly stronger in these counties, as awareness translates more readily into search activity when households face lower search costs. These results lend support to the argument, as in Drechsler et al. (2017) and others, that banks enjoy greater market power when serving financially unsophisticated customers, enabling them to offer lower rates on deposits with low risk of fund outflows. Consequently, financial sophistication appears to play a central role in amplifying the influence of online social networks on deposit pricing.

[**Insert Table 4, here**]

Given that higher financial sophistication is typically associated with more active online social engagement (Gambacorta et al. 2023), this dynamic serves to intensify 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.

5.5 Robustness tests

In this section, we offer additional robustness tests to preclude alternative channels such as geographical and economic proximity that could explain our findings. Furthermore, we incorporate time-varying data on residential fixed broadband connections to validate that the observed effects are driven by *active* social connections between households.

5.5.1 *Geographical proximity*

The validity of our empirical identification strategy relies on the assumption that socially connected counties are geographically and administratively distinct from the focal county. While our baseline specifications already control for geographic distance using a distance-weighted measure of deposit rates (DDR), we further test whether social proximity acts as a separate channel from geographical proximity for the transmission of changes in small banks deposit pricing. To do so, we re-estimate our main specifications after excluding all counties within a 25-mile radius from the focal county c from the calculation of the social-connections weighted variables in eqs.(4)-(5). This exclusion ensures that the remaining socially connected counties are sufficiently distant, thereby isolating the role of social networks.

Tables 5 and 6 replicate the analyses presented in Tables 3 and 4, respectively, using this restricted sample. The results remain broadly consistent with our main findings, although the statistical significance of the interaction effects between SDR and both competition and financial sophistication dummies is weaker for certain deposit rate products.[13]

[Insert Table 5 and Table 6, here]

5.5.2 *Economic proximity*

Economic proximity, in the sense of economic linkages between counties due to similarities in industry composition could be an alternative mechanism that explains the above findings. The rationale is that counties with similar industrial structures may exhibit stronger social ties, such as through trade, labor mobility, or migration patterns. We follow Flynn & Wang (2025), and calculate economic linkages based on industry composition. Specifically, we measure a county's industry composition using employment data by industry from the Bureau of Labor Statistics' (BLS) Quarterly Census of Employment and Wages. For each county-year, we calculate the share of total county employment in each 2-digit NAICS sector

[13] In the Online Appendix, we present the results excluding counties within a 50-mile radius from the focal county c. The main effects remain largely similar but the interaction terms, while still positive, are statistically insignificant.

and compute the cosine similarity of industry employment shares for each county pair in each year, 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:

$$EPDR_{c,t} = \sum_{j \in C-c} EP_{c,j,t} \times \Delta r_{j,t} \tag{8}$$

where $EP_{c,j,t}$ is the industry cosine similarity between county c and j.

Columns (1)-(4) in Table (7) show that, after including *Economic Proximity Deposit Rate* in our baseline specifications, the coefficient on our main variable of interest, *Social Deposit Rate*, remains positive and statistically significant while the coefficient of *EPDR* is also positive and significant. This suggests that social ties and economic linkages are two separate channels affecting deposit rate activity.

[Insert Table 7, here]

5.5.3 Residential broadband connections

To capture digital access and internet penetration at the local level, we incorporate residential fixed broadband connections as a proxy for household connectivity. Higher values of this variable indicate greater internet access, which likely facilitates peer interaction through online social networks, a necessary condition for the social-ties deposit rate channel. We obtain county-level data from the Federal Communications Commission (FCC) Internet Access Services Speed Tier dataset.

Specifically, to account for internet access in our identification strategy, we recalculate both the *SDR* and the *SLBMS* as follows:

$$SDR^{rob}_{c,t} = I_{c,t} \times \sum_{j \in C-c} SCI_{c,j} \times I_{j,t} \times \Delta r_{j,t} \tag{9}$$

$$SLBMS^{rob}_{c,t} = I_{c,t} \times \sum_{j \in C-c} SCI_{c,j} \times I_{j,t} \times \Delta LBMS_{j,t} \tag{10}$$

where $I_{c,t}$ and $I_{j,t}$ are indicator variables equal to one if more than 40% of households in county c or county j, respectively, have residential fixed broadband connections with a downstream speed of at least 10 Mbps, and zero otherwise.[14]

This approach leverages temporal variation in residential broadband connections as a proxy for local household activity on social media platforms. By definition, social connections between counties c and j are included in the calculation of $SDR^{rob}_{c,t}$ only when both counties exceed the broadband threshold, ensuring that the measure varies over time in association with meaningful digital connectivity, reflecting *active* digital social ties. Results presented in columns (5)-(8) of Table 7 show that our main findings remain robust when we use $SDR^{rob}_{c,t}$ supporting our interpretation that online social networks that facilitate the exchange of information serve as a key transmission channel for deposit rate shocks.

6 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 these findings, we now examine empirically a corollary: as social network engagement among customers of small banks intensifies, deposit rates across all socially connected counties will 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 empirically 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, as for example GDP per capita, grow faster than

[14] The 40% threshold is based on FCC data categorization, which splits the population into five tiers ranging from 0-20% to 80-100%. Similar results are obtained if use an alternative 60% threshold.

those with higher levels and thus, eventually converging over time (Barro & Sala-i Martin 1992, Kremer, Willis & You 2022).

The simplest β-convergence model is:

$$\Delta Y_{i,t} = \alpha + \beta Y_{i,t-1} + \epsilon_{i,t} \tag{11}$$

where Y is the outcome 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 outcome variable 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, $r^{sc}_{c,t}$, defined as:

$$r^{sc}_{c,t} = \sum_{j \in C-c} \frac{SCI_{c,j}}{\sum_{j \in C-c} SCI_{c,j}} r_{j,t}$$

The outcome variable becomes:

$$\Delta(r_{c,t} - r^{sc}_{c,t}) = (r_{c,t} - r^{sc}_{c,t}) - (r_{c,t-1} - r^{sc}_{c,t-1})$$

Although our SCI data is available as a snapshot of 2020 Facebook links, its time-invariance did not pose a limitation for our earlier Bartik-type, share-shift instrument, which relies on the stability of shares. However, our current objective is to test whether the increasing use of social networks accelerates the convergence of deposit rate changes of small banks. To capture time-variation in the intensity of social network usage, we define:

$$SC_{c,t-1} = \sum_{j \in C-c} SCI_{c,j} \times U_t$$

where U_t is the total number of Facebook users at time t across all US counties.[15] Over this period, Facebook's total monthly active users in the US (and Canada) increased from 163 million to 271 million, a 66% increase.[16] This substantial growth in user engagement provides

[15] 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.

[16] Facebook monthly active users data is downloaded from Statista https://www.statista.com/

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:

$$\Delta(r_{c,t}-r^{sc}_{c,t}) = \alpha_1 SC_{c,t-1}+\alpha_2 SC_{c,t-1}\times(r_{c,t-1}-r^{sc}_{c,t-1})+\beta(r_{c,t-1}-r^{sc}_{c,t-1})+x_{c,t}+f_c+f_t+\epsilon_{c,t} \quad (12)$$

This difference-in-differences (DiD) specification in a panel data context allows for a causal interpretation by removing both county-specific and common temporal trends. The use of first differences in the dependent variable removes any macroeconomic shocks or policy changes, while county fixed effects absorb any unobserved heterogeneity such as persistent differences in local economic conditions or in banking market structures. The parameter of interest is α_2. A negative sign implies that counties with deposit rates above the weighted average of their social peers tend to reduce rates more rapidly as social connectivity intensifies, and vice versa. This provides a direct test of whether social networks accelerate convergence toward a common deposit rate equilibrium.

The negative and statistically significant estimate of α_2 in columns (1)-(4) of Table 8 provides clear evidence that social connections accelerate convergence in deposit rates among small banks. The only exception is for the money market accounts in column (4), where the coefficient is negative but insignificant. At the same time, the negative and statistically significant estimate of β suggests that convergence is taking place beyond social network spillovers. This could be partially explained by structural changes in the banking sector, including consolidation among small and medium-sized banks, which made small banks adopt business models resembling those of multi-market banks. Additionally, the rise of online banks, whose pricing strategies go beyond local market geographic boundaries, exerts competitive pressure on local banks to revise their deposit rates. The growth of the internet

statistics/247614/number-of-monthly-active-facebook-users-worldwide/.

further facilitates the transmission of financial information, reinforcing uniform pricing behaviour. Taken together, our empirical results show that while multiple forces contribute to deposit rate convergence of small banks, social networks play a key and distinct role in accelerating this process.

[Insert Table 8, here]

To further investigate the moderating role of market concentration of small banks, we extend our model by introducing a triple interaction between social connectivity, the deposit rate gap, and the high competition dummy. The specification is given by:

$$\begin{aligned}\Delta(r_{c,t} - r^{sc}_{c,t}) = {} & \alpha_1 SC_{c,t-1} + \alpha_2 SC_{c,t-1} \times (r_{c,t-1} - r^{sc}_{c,t-1}) \\ & + \alpha_3 SC_{c,t-1} \times HighComp + \beta_1 (r_{c,t-1} - r^{sc}_{c,t-1}) \\ & + \beta_2 (r_{c,t-1} - r^{sc}_{c,t-1}) \times HighComp \\ & + \alpha_4 SC_{c,t-1} \times (r_{c,t-1} - r^{sc}_{c,t-1}) \times HighComp \\ & + x_{c,t} + f_c + f_t + \epsilon_{c,t} \end{aligned} \tag{13}$$

The estimate of α_4 in columns (5)-(8) in Table 8 is negative and statistically significant, indicating that convergence is particularly pronounced in counties with high competition between small banks. This effect holds even for money market accounts, which previously showed no significance. The interaction term α_2 is generally insignificant, suggesting that competitive dynamics are crucial for social spillovers to translate into pricing convergence.

We also examine the net convergence effect independent of social network effects, defined as $\beta = (\beta_1 + \beta_2 \times HighComp)$. For example, for 6-month deposits, the estimated effect is $\beta_1 = -0.11$ for low competition markets ($HighComp = 0$) and $\beta_1 + \beta_2 = -0.11 + 0.070 = -0.04$ in high competition markets. These findings suggest that small banks' deposit rate convergence takes place even without social network effects, though the magnitude is attenuated in more competitive markets. This may reflect the tendency of small banks in competitive markets to prioritize local pricing strategies, partially offsetting, but not reversing, broader uniform pricing pressures.

To address concerns that our results are driven by geographic proximity of small banks, we repeat the above analysis after excluding counties within 25 miles from the calculation of $r^{sc}_{c,t}$. The results, presented in Table 9, are economically and statistically consistent with those in Table 8.[17]

[Insert Table 9, here]

Finally, we apply the same panel model (12) to deposit rates of large banks. As shown in columns (1)-(4) of Table 10, the coefficient α_2 is statistically insignificant across all specifications with the exception of money market rates, indicating limited evidence that social connectivity drives 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 literature 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). The absence of social network spillover effects on this context may reflect the centralised decision making of large banks, where regional branches of large multi-market banks transmit financial information to central rate-setting branch which then determines a uniform rate across all regions.

[Insert Table 10, here]

Overall, our findings underscore that increased social connectivity accelerates convergence towards common deposit rates, effectively diminishing regional pricing disparities of small banks. This mechanism operates in parallel with broader convergence in bank deposit rates observed across large and small banks, possibly due to technological advancements that reduce the relevance of geographic distance in banking.

[17] Additional robustness checks in the Online Appendix Table, excluding counties within 50 miles further confirm that geographical proximity is not the primary driver of uniform pricing.

7 Conclusions

We introduce a novel determinant of local deposit rates and banks' pricing power: social networks. While prior research has established social connections as a key driver of consumer decision-making, we demonstrate that these ties serve as a distinct channel for transmitting valuable financial insights, shaping deposit pricing behaviour, particularly among small banks.

First, we confirm previous findings that large banks tend to price deposits uniformly, while we provide new evidence that small banks adjust deposit rates based on changes in local market conditions, especially in highly competitive markets. Following a merger-induced branch closure by a large bank, small banks respond by offering higher rates to attract depositors while other large banks do not respond. This differential behavior is consistent with the literature assertion that small banks' customer base and business models are very different to those of large banks.

Second, leveraging exogenous shifts in local market structure across socially connected counties, we show that deposit pricing decisions of small banks in a focal area are influenced by deposit rate changes that occur in other counties through social connections. Our measure of *social proximity of deposit rates*, constructed from county-level data on social networks, captures these spillovers while controlling for geographic and economic proximity. Moreover, we highlight the role of market competition as a lever of market power that reinforces the effect of social ties on deposit rates. Robustness checks confirm that the effect takes into account *active* social connections.

Third, we isolate the social networks spillover effect by incorporating a proxy for financial sophistication combining educational attainment and stock market participation. We find that banks serving more-sophisticated customers have lower pricing power, as these customers are more likely to engage in financial information exchange through their social networks. They are also more likely to act upon the financial information by seeking to improve the returns from their deposits.

Finally, we explore the long-run implication of these dynamics for the convergence toward a homogeneous rate among small banks in socially connected counties. Interestingly, we find that the deposit rate gap between banks and their social peers narrows over time as new technologies reduce the importance of geographic distance. However, while both small and large banks rates exhibit convergence over time, only small banks rates show a clear acceleration driven by social spillovers–validating our core hypothesis.

Our findings underscore the growing importance of online social networks in shaping deposit rate policies and offer new insights into the behavioral forces driving local banking competition. Social networks emerge as a complementary and increasingly powerful dimension of deposit market dynamics. As small banks respond more to local and socially transmitted competitive pressures, the transmission of monetary policy through the deposit rate channel may have uneven effects across bank types. This highlights the need to account for new informational channels when assessing the pass-through of rate changes. In socially connected regions, deposit rate changes, whether driven by policy changes or competitive dynamics, might ripple across geographically distant markets, amplifying the reach of monetary interventions. As social connectedness increases, small banks deposit rates converge across connected counties and this convergence, accelerated by digital technologies, suggests that geographic barriers to monetary transmission are diminishing.

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Tables

Table 1. Small bank deposit rate changes after large bank branch closure
The table reports coefficient estimates and robust standard errors (in parentheses) from second stage regressions. In the first stage (see Appendix), merger-induced large bank branch closures are used as an instrument for the loss of market share of large banks $\Delta LBMS$. The dependent variable is the change in rates of deposits of different sizes and maturities for small banks (6m10K, 12m10k, 12m10k and mm10k). Estimation method is 2SLS with time and county fixed effects. The under-identification F-test is 262.25*** and the robust to clustered errors F statistic for weak identification is 322.80***. The sample period is 2012-2023. The lower part of the table also reports the number of observations. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) 6m10K	(2) 12m10K	(3) 12m100K	(4) mm10k	(5) 6m10K	(6) 12m10K	(7) 12m100K	(8) mm10k
$\Delta LBMS$	0.851***	0.822**	0.900**	0.351***	0.103	0.109	0.346	0.138
	(0.321)	(0.373)	(0.385)	(0.128)	(0.272)	(0.326)	(0.335)	(0.112)
$\Delta LBMS \times HighComp$					2.623***	2.502**	1.935*	0.742**
					(0.976)	(1.106)	(1.135)	(0.377)
SBHHI	0.100	0.118	0.084	0.013	0.019	0.040	0.024	-0.010
	(0.099)	(0.119)	(0.122)	(0.042)	(0.102)	(0.122)	(0.125)	(0.042)
Seniors	1.723**	0.085	0.151	0.471	1.732**	0.092	0.159	0.473
	(0.774)	(0.878)	(0.907)	(0.332)	(0.777)	(0.880)	(0.908)	(0.333)
Population	0.000	-0.005*	-0.004	0.003**	-0.000	-0.005*	-0.004	0.003**
	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)	(0.003)	(0.003)	(0.001)
Realgdppc	0.000	0.001	0.001	0.000**	0.000	0.001	0.001	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FSophistication	0.012**	0.008	0.006	0.000	0.012**	0.008	0.006	0.000
	(0.006)	(0.007)	(0.007)	(0.002)	(0.006)	(0.007)	(0.007)	(0.002)
Obs.	29,318	29,348	29,280	29,170	29,318	29,348	29,280	29,170

Table 2. Large bank deposit rate changes after large bank branch closure
The table reports coefficient estimates and robust standard errors (in parentheses) from second stage regressions. In the first stage (see Appendix), merger-induced large bank branch closures are used as an instrument for the loss of the market share of large banks ($LBMS$). The dependent variable is the change in rates of deposits of different sizes and maturities for large banks (6m10K, 12m10k, 12m10k and mm10k). Estimation method is 2SLS with time and county fixed effects. The under-identification F-test is 170.24*** and the robust to clustered errors F statistic for weak identification is 196.97***. The sample period is 2012-2023. The lower part of the table also reports the number of observations. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) 6m10K	(2) 12m10K	(3) 12m100K	(4) mm10k
$\Delta LBMS$	0.702***	0.402	0.112	0.110
	(0.244)	(0.278)	(0.330)	(0.086)
SBHHI	0.183**	0.072	0.032	0.006
	(0.086)	(0.089)	(0.111)	(0.019)
Seniors	-1.736**	2.768***	3.021**	0.017
	(0.823)	(0.992)	(1.184)	(0.155)
Population	-0.003**	-0.000	0.001	-0.002***
	(0.001)	(0.002)	(0.002)	(0.000)
Realgdppc	0.002***	-0.000	0.001	0.000
	(0.000)	(0.001)	(0.001)	(0.000)
FSophistication	0.006	0.011**	0.011*	-0.003***
	(0.005)	(0.005)	(0.006)	(0.001)
Obs.	17,135	17,125	17,042	16,264

Table 3. Social connections and small bank deposit rate changes

The table reports coefficient estimates and robust standard errors (in parentheses) from second stage regressions. In the first stage (see Appendix), the variable *Social Large-bank Branch Closure* is used as an instrument for the *Social Deposit Rate*. The dependent variable is the change in (small banks) rates of deposits of different sizes and maturities (6m10K, 12m10k, 12m10k and mm10k). Estimation method is 2SLS with time and county fixed effects. The under-identification F-test is 108.32*** and the robust to clustered errors F statistic for weak identification is 105.60***. The sample period is 2016-2023. The lower part of the table also reports the number of observations. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) 6m10K	(2) 12m10K	(3) 12m100K	(4) mm10k	(5) 6m10K	(6) 12m10K	(7) 12m100K	(8) mm10k
SDR	1.461***	1.340***	1.386***	1.306***	1.406***	1.314***	1.361***	1.239***
	(0.248)	(0.248)	(0.255)	(0.227)	(0.233)	(0.239)	(0.246)	(0.214)
SDR × *HighComp*					0.811**	0.606*	0.630*	0.917**
					(0.339)	(0.323)	(0.329)	(0.409)
DDR	0.025*	0.010	0.004	0.057***	0.007	-0.003	-0.011	0.035
	(0.015)	(0.013)	(0.014)	(0.018)	(0.020)	(0.018)	(0.019)	(0.024)
SBHHI	0.022	-0.023	-0.102	-0.022	0.013	-0.037	-0.120	-0.030
	(0.145)	(0.172)	(0.179)	(0.057)	(0.145)	(0.173)	(0.180)	(0.057)
Seniors	0.315	-0.754	-0.766	-0.099	-0.209	-1.100	-1.133	-0.291
	(1.308)	(1.525)	(1.585)	(0.522)	(1.279)	(1.490)	(1.553)	(0.524)
Population	0.009	-0.001	0.002	0.005*	0.007	-0.003	0.000	0.004
	(0.007)	(0.009)	(0.010)	(0.003)	(0.007)	(0.009)	(0.009)	(0.003)
Realgdppc	0.001	0.001*	0.001*	0.001**	0.001	0.001*	0.002**	0.001***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
FSophistication	0.012	0.011	0.009	-0.002	0.013	0.012	0.010	-0.002
	(0.009)	(0.011)	(0.012)	(0.004)	(0.009)	(0.011)	(0.012)	(0.004)
Obs.	17,162	17,191	17,152	17,055	17,162	17,191	17,152	17,055

Table 4. Social connections, small bank deposit rate changes and financial sophistication
The table reports coefficient estimates and robust standard errors (in parentheses) from second stage regressions. In the first stage (see Appendix), the variable *Social Large-bank Branch Closure* is used as an instrument for the *Social Deposit Rate*. The dependent variable is the change in rates of deposits of different sizes and maturities (6m10K, 12m10k, 12m10k and mm10k). Estimation method is 2SLS with time and county fixed effects. The under-identification F-test is 111.65*** and the robust to clustered errors F statistic for weak identification is 53.71***. The sample period is 2016-2023. The lower part of the table also reports the number of observations. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) 6m10K	(2) 12m10K	(3) 12m100K	(4) mm10k
SDR	0.461	0.601	0.768*	0.938*
	(0.462)	(0.425)	(0.442)	(0.499)
SDR $\times$ *HighSoph*	0.854**	0.638**	0.533*	0.339
	(0.335)	(0.296)	(0.300)	(0.428)
DDR	0.066***	0.042**	0.030	0.074***
	(0.023)	(0.020)	(0.021)	(0.027)
SBHHI	0.034	-0.036	-0.116	-0.028
	(0.151)	(0.177)	(0.182)	(0.058)
Seniors	-1.239	-2.112	-1.913	-0.329
	(1.510)	(1.702)	(1.751)	(0.598)
Population	0.006	-0.004	-0.000	0.005*
	(0.007)	(0.009)	(0.009)	(0.003)
Realgdppc	0.002**	0.002**	0.002**	0.001***
	(0.001)	(0.001)	(0.001)	(0.000)
FSophistication	0.025**	0.023*	0.020	-0.001
	(0.011)	(0.013)	(0.013)	(0.004)
Obs.	17,162	17,191	17,152	17,055

Table 5. Social connections and small bank deposit rate changes - 25miles radius
The table reports coefficient estimates and robust standard errors (in parentheses) from second stage regressions. In the first stage (see Appendix), the variable *Social Large-bank Branch Closure* is used as an instrument for the *Social Deposit Rate*. The dependent variable is the change in rates of deposits of different sizes and maturities for small banks (6m10K, 12m10k, 12m10k and mm10k). Estimation method is 2SLS with time and county fixed effects. The under-identification F-test is 156.08*** and the robust to clustered errors F statistic for weak identification is 162.62***. The sample period is 2016-2023. The lower part of the table also reports the number of observations. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) 6m10K	(2) 12m10K	(3) 12m100K	(4) mm10k	(5) 6m10K	(6) 12m10K	(7) 12m100K	(8) mm10k
SDR	1.183***	1.205***	1.223***	1.250***	1.109***	1.162***	1.180***	1.132***
	(0.228)	(0.244)	(0.250)	(0.216)	(0.216)	(0.235)	(0.241)	(0.211)
SDR × *HighComp*					0.813**	0.626*	0.677**	1.217***
					(0.360)	(0.325)	(0.327)	(0.454)
SBHHI	0.126	0.055	-0.025	0.004	0.115	0.040	-0.042	-0.006
	(0.141)	(0.170)	(0.175)	(0.057)	(0.141)	(0.171)	(0.176)	(0.057)
Seniors	0.389	-1.139	-1.188	-0.011	-0.135	-1.504	-1.584	-0.274
	(1.229)	(1.438)	(1.483)	(0.511)	(1.222)	(1.417)	(1.465)	(0.522)
Population	0.008	-0.003	-0.001	0.006**	0.005	-0.005	-0.003	0.005*
	(0.006)	(0.008)	(0.009)	(0.003)	(0.006)	(0.008)	(0.008)	(0.003)
Realgdppc	0.001	0.001	0.001	0.000**	0.001	0.001	0.001	0.001**
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
FSophistication	0.016*	0.015	0.013	-0.002	0.018**	0.016	0.015	-0.001
	(0.009)	(0.011)	(0.011)	(0.004)	(0.009)	(0.011)	(0.011)	(0.004)
Obs.	17,162	17,191	17,152	17,055	17,162	17,191	17,152	17,055

Table 6. Social connections, small bank deposit rate changes and financial sophistication - 25miles radius

The table reports coefficient estimates and robust standard errors (in parentheses) from second stage regressions. In the first stage (see Appendix), the variable *Social Large-bank Branch Closure* is used as an instrument for the *Social Deposit Rate*. The dependent variable is the change in rates of deposits of different sizes and maturities for small banks (6m10K, 12m10k, 12m10k and mm10k). Estimation method is 2SLS with time and county fixed effects. The under-identification F-test is 207.89*** and the robust to clustered errors F statistic for weak identification is 105.55***. The sample period is 2016-2023. The lower part of the table also reports the number of observations. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) 6m10K	(2) 12m10K	(3) 12m100K	(4) mm10k
SDR	0.608	0.509	0.632	1.263***
	(0.429)	(0.424)	(0.432)	(0.472)
SDR × *HighSoph*	0.514	0.618**	0.522*	-0.012
	(0.324)	(0.300)	(0.299)	(0.433)
SBHHI	0.125	0.047	-0.032	0.005
	(0.144)	(0.174)	(0.179)	(0.057)
Seniors	-0.371	-2.176	-2.082	-0.004
	(1.361)	(1.586)	(1.616)	(0.560)
Population	0.008	-0.003	-0.001	0.006**
	(0.006)	(0.008)	(0.008)	(0.003)
Realgdppc	0.001	0.002*	0.002*	0.000*
	(0.001)	(0.001)	(0.001)	(0.000)
FSophistication	0.023**	0.025**	0.022*	-0.002
	(0.010)	(0.012)	(0.013)	(0.004)
Obs.	17,162	17,191	17,152	17,055

Table 7. Social connections, small bank deposit rate changes - Economic Proximity and Internet Access

The table reports coefficient estimates and robust standard errors (in parentheses) from second stage regressions. In columns (1)-(4), In the first stage (see Appendix), the variable *Social Large-bank Branch Closure* is used as an instrument for the *Social Deposit Rate* and we additionally control for economic connections between counties. In columns (5)-(8), In the first stage (see Appendix), the variable $SLBMS^{rob}$ is used as an instrument for the SDR^{rob}, where we correct for residential fixed broadband connections. The dependent variable is the change in rates of deposits of different sizes and maturities (6m10K, 12m10k, 12m10k and mm10k). Estimation method is 2SLS with time and county fixed effects. Estimation method is 2SLS with time and county fixed effects. The under-identification F-test is 105.99*** and the robust to clustered errors F statistic for weak identification is 103.51***. The sample period is 2016-2023. The lower part of the table also reports the number of observations. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) 6m10K	(2) 12m10K	(3) 12m100K	(4) mm10k	(5) 6m10K	(6) 12m10K	(7) 12m100K	(8) mm10k
SDR	1.477***	1.364***	1.412***	1.325***	0.817***	1.047***	1.064***	0.629*
	(0.252)	(0.254)	(0.261)	(0.232)	(0.284)	(0.292)	(0.291)	(0.323)
DDR	0.021	0.006	-0.002	0.053***	0.070***	0.040***	0.035***	0.117***
	(0.016)	(0.014)	(0.015)	(0.019)	(0.013)	(0.011)	(0.011)	(0.018)
EPDR	0.283***	0.263***	0.284***	0.261**				
	(0.090)	(0.088)	(0.088)	(0.103)				
SBHHI	-0.001	-0.050	-0.133	-0.030	0.151	0.096	0.020	0.016
	(0.146)	(0.174)	(0.181)	(0.058)	(0.144)	(0.173)	(0.179)	(0.057)
Seniors	0.293	-0.703	-0.698	-0.097	-0.443	-1.509	-1.539	-0.445
	(1.293)	(1.518)	(1.577)	(0.520)	(1.236)	(1.474)	(1.518)	(0.513)
Population	0.007	-0.003	0.000	0.005*	0.001	-0.007	-0.004	0.002
	(0.007)	(0.009)	(0.010)	(0.003)	(0.006)	(0.008)	(0.009)	(0.003)
Realgdppc	0.001*	0.002**	0.002**	0.001***	0.001	0.001	0.001	0.001**
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
FSophistication	0.014	0.013	0.012	-0.002	0.026***	0.026**	0.026**	0.002
	(0.009)	(0.011)	(0.011)	(0.003)	(0.009)	(0.011)	(0.011)	(0.004)
Obs.	17,162	17,191	17,152	17,055	17,162	17,191	17,152	17,055

Table 8. Use of social media and small banks uniform pricing

The table reports coefficient estimates and robust standard errors (in parentheses) from difference-in-difference regressions. The dependent variable is the change in the distance between (small banks) rates of deposits of different sizes (6m10K, 12m10k, 12m10k and mm10k) and maturities and the weighted average of deposit rates of social peers. Estimation method is OLS with time and county fixed effects. The data frequency is quarterly and the sample period is 2011q2-2023q3. The lower part of the table also reports the number of observations. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) 6m10K	(2) 12m10K	(3) 12m100K	(4) mm10k	(5) 6m10K	(6) 12m10K	(7) 12m100K	(8) mm10k
$SC \times (r_{c,t-1} - r^{sc}_{c,t-1})$	-0.002***	-0.001***	-0.001***	-0.000	-0.001**	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$SC \times (r_{c,t-1} - r^{sc}_{c,t-1}) \times HighComp$					-0.006***	-0.004***	-0.002**	-0.003***
					(0.001)	(0.001)	(0.001)	(0.001)
$(r_{c,t-1} - r^{sc}_{c,t-1})$	-0.088***	-0.109***	-0.086***	-0.113***	-0.110***	-0.125***	-0.107***	-0.117***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.007)	(0.006)	(0.005)	(0.005)
$(r_{c,t-1} - r^{sc}_{c,t-1}) \times HighComp$					0.070***	0.051***	0.051***	0.024***
					(0.011)	(0.010)	(0.009)	(0.009)
SC	0.001***	0.001**	0.001**	0.000***	0.001***	0.001***	0.001**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$SC \times HighComp$				0.002***	0.001**	0.001**	0.001***	
					(0.001)	(0.001)	(0.001)	(0.000)
$SBHHI$	-0.010*	-0.014*	-0.018**	-0.004	-0.010	-0.014*	-0.018**	-0.003
	(0.006)	(0.008)	(0.008)	(0.003)	(0.006)	(0.008)	(0.008)	(0.003)
$Seniors$	-0.182***	-0.168***	-0.159***	-0.063***	-0.166***	-0.156***	-0.147***	-0.055***
	(0.043)	(0.050)	(0.053)	(0.019)	(0.042)	(0.050)	(0.053)	(0.019)
$Population$	0.008	0.017*	0.019**	0.016***	0.007	0.016*	0.019**	0.016***
	(0.008)	(0.009)	(0.010)	(0.004)	(0.008)	(0.009)	(0.009)	(0.004)
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)	(0.000)	(0.000)	(0.000)	(0.000)
$FSophistication$	0.001	-0.001	-0.002	-0.000	0.001	-0.001	-0.002	-0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
$Constant$	-0.003	-0.032	-0.042	-0.047***	-0.007	-0.037	-0.046	-0.050***
	(0.032)	(0.037)	(0.038)	(0.015)	(0.031)	(0.037)	(0.038)	(0.015)
Obs.	143,461	143,555	144,811	142,890	143,461	143,555	144,811	142,890

Table 9. Use of social media and small banks uniform pricing - 25miles radius
The table reports coefficient estimates and robust standard errors (in parentheses) from difference-in-difference regressions. The dependent variable is the change in the distance between (small banks) rates of deposits of different sizes and maturities (6m10K, 12m10k, 12m10k and mm10k) and the weighted average of deposit rates of social peers. Estimation method is OLS with time and county fixed effects. The data frequency is quarterly and the sample period is 2011q2-2023q3. The lower part of the table also reports the number of observations. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) 6m10K	(2) 12m10K	(3) 12m100K	(4) mm10k	(5) 6m10K	(6) 12m10K	(7) 12m100K	(8) mm10k
$SC \times (r_{c,t-1} - r^{sc}_{c,t-1})$	-0.002***	-0.001***	-0.001***	-0.000	-0.001**	-0.001**	-0.001**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$SC \times (r_{c,t-1} - r^{sc}_{c,t-1}) \times HighComp$					-0.008***	-0.006***	-0.004***	-0.003***
					(0.001)	(0.001)	(0.001)	(0.001)
$(r_{c,t-1} - r^{sc}_{c,t-1})$	-0.086***	-0.104***	-0.081***	-0.112***	-0.103***	-0.118***	-0.098***	-0.116***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.006)	(0.005)	(0.005)	(0.005)
$(r_{c,t-1} - r^{sc}_{c,t-1}) \times HighComp$					0.070***	0.054***	0.051***	0.023***
					(0.011)	(0.010)	(0.009)	(0.009)
SC	0.001***	0.001***	0.001**	0.000***	0.001***	0.001***	0.001***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$SC \times HighComp$					0.002***	0.002***	0.002**	0.001***
					(0.001)	(0.001)	(0.001)	(0.000)
SBHHI	-0.012*	-0.016*	-0.019**	-0.004	-0.012*	-0.015*	-0.019**	-0.004
	(0.006)	(0.008)	(0.008)	(0.003)	(0.006)	(0.008)	(0.008)	(0.003)
Seniors	-0.187***	-0.184***	-0.182***	-0.063***	-0.173***	-0.173***	-0.171***	-0.057***
	(0.044)	(0.051)	(0.054)	(0.019)	(0.043)	(0.051)	(0.054)	(0.019)
Population	0.012	0.019**	0.020**	0.018***	0.010	0.018*	0.019**	0.017***
	(0.008)	(0.009)	(0.010)	(0.004)	(0.008)	(0.009)	(0.010)	(0.004)
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)	(0.000)	(0.000)	(0.000)	(0.000)
FSophistication	0.000	-0.001	-0.002**	-0.000	0.000	-0.001	-0.002*	-0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Constant	-0.015	-0.039	-0.041	-0.053***	-0.015	-0.041	-0.042	-0.054***
	(0.032)	(0.037)	(0.038)	(0.015)	(0.031)	(0.037)	(0.038)	(0.015)
Obs.	143,461	143,555	144,811	142,890	143,461	143,555	144,811	142,890

Table 10. Use of social media and large banks uniform pricing
The table reports coefficient estimates and robust standard errors (in parentheses) from difference-in-difference regressions. The dependent variable is the change in the distance between (small banks) rates of deposits of different sizes and maturities (6m10K, 12m10k, 12m10k and mm10k) and the weighted average of deposit rates of social peers. Estimation method is OLS with time and county fixed effects. The data frequency is quarterly and the sample period is 2011q2-2023q3. The lower part of the table also reports the number of observations. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) 6m10K	(2) 12m10K	(3) 12m100K	(4) mm10k
$SC \times (r_{c,t-1} - r^{sc}_{c,t-1})$	0.001*	0.001	0.000	-0.002**
	(0.000)	(0.000)	(0.000)	(0.001)
$(r_{c,t-1} - r^{sc}_{c,t-1})$	-0.054***	-0.078***	-0.081***	-0.100***
	(0.005)	(0.004)	(0.004)	(0.005)
SC	0.001***	0.001***	0.002***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$SBHHI$	-0.002	-0.004	-0.005	0.001
	(0.004)	(0.004)	(0.005)	(0.001)
$Seniors$	0.005	0.022	0.064	0.008
	(0.033)	(0.037)	(0.051)	(0.008)
$Population$	0.063***	0.033***	0.057***	0.005***
	(0.006)	(0.007)	(0.008)	(0.001)
$Realgdppc$	0.000***	0.000***	0.000***	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
$FSophistication$	-0.002**	-0.001*	-0.002**	-0.000
	(0.001)	(0.001)	(0.001)	(0.000)
Constant	-0.268***	-0.146***	-0.257***	-0.020***
	(0.027)	(0.030)	(0.039)	(0.006)
Obs.	91,068	91,079	91,826	87,787

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 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, informed depositors become price-sensitive (they can switch if another bank offers 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 aggregate elasticity of deposit demand to interest rates 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

$$\mu_A = \alpha \, w_{BA} \, \Delta r_A, \tag{A1}$$

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

A depositor becomes *aware* of the event if she encounters at least one such post. Hence, the probability of awareness is

$$p(\mu_A) = p(w_{BA}, \Delta r_A) = 1 - \exp[-\alpha \, w_{BA} \, \Delta r_A]. \tag{A2}$$

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 faces demand

$$D_i = a - b \, r_i + d \, \bar{r}_{-i} + \eta \, m, \tag{A3}$$

where $\bar{r}_{-i}$ is the average rate of competitors, and $m \in [0, 1]$ denotes the share of depositors who actively search. The parameters (a, b, d, η) capture the size and elasticity of deposit demand. The degree of product substitutability among banks is denoted by $\theta \equiv d/b \in [0, 1)$; it governs how sensitive a bank's demand is to competitors' rates and thus the degree of local competition[18].

The term ηm is a demand-shifter: as the share of depositors who actively search m rises, the deposit demand at each bank increases by η for each additional depositor searching (all else equal). Intuitively, when more depositors search and compare offers, then the effective size of the contestable depositor pool grows, raising banks' demand for deposits (or raising

[18] 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).

banks' sensitivity to rate setting). In other words, m shifts the demand curve outward (upwards) for all banks in that market, making deposits more contestable.

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

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 (inattentive) demand and post the baseline rate

$$r = r_0.$$

In this benchmark, parameters governing search activation or pass-through – the sophistication share λ, search costs (c_L, c_H), and competition intensity (N_B, θ) – 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 (price-sensitive) depositors, each of the N_B symmetric banks in county B chooses its deposit rate r_i to maximize

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

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

$$(2b - d)r = bR + a + \eta m. \tag{A4}$$

Hence, the equilibrium rate is

$$r^*(m) = \frac{bR + a + \eta m}{2b - d} = \frac{R + \frac{a}{b} + \frac{\eta m}{b}}{2 - \theta}, \qquad \theta \equiv \frac{d}{b} \in [0, 1). \tag{A5}$$

Proposition 1 (Deposit-market equilibrium)**.** *The equilibrium deposit rate increases in the fraction of active searchers,*

$$\frac{\partial r^*(m)}{\partial m} = \frac{\eta}{2b - d} > 0.$$

Moreover, competition amplifies the pass-through from depositor activation to rates:

$$\frac{\partial^2 r^*(m)}{\partial m\,\partial \theta} = \frac{\eta b}{(2b - d)^2} > 0.$$

Intuitively, stronger substitutability among banks (higher θ) lowers equilibrium markups. Consequently, any increase in price sensitivity induced by depositors' search translates into a larger rise in deposit rates.

Depositors' search behavior

Aware depositors can obtain the competitive rate $r^*(m)$ rather than the inattentive benchmark r_0. The expected benefit from search is

$$B(m) = \beta\,[r^*(m) - r_0],$$

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

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

$$m = p(w_{BA}, \Delta r_A)\,[\lambda\,\mathbf{1}\{B(m) \geq c_L\} + (1-\lambda)\,\mathbf{1}\{B(m) \geq c_H\}]\,. \tag{A6}$$

Proposition 2 (Search equilibrium)**.** *There exists a fixed point $m^* \in [0,1]$ satisfying (A6):*

$$m^* = \begin{cases} 0, & \text{if } p < \dfrac{c_L}{\beta\,[r^*(0) - r_0]}, \\ p\,\lambda, & \text{if } \dfrac{c_L}{\beta\,[r^*(0) - r_0]} \leq p < \dfrac{c_H}{\beta\,[r^*(0) - r_0]}, \\ p, & \text{if } p \geq \dfrac{c_H}{\beta\,[r^*(0) - r_0]}. \end{cases}$$

Conditional on activation, m^* is increasing in awareness p, sophistication λ, and competition θ.

Thus, search activity is initiated ($m^* > 0$) if and only if the probability of awareness is high enough $p(w_{BA}, \Delta r_A) \geq \bar{p} \equiv \frac{c_L}{\beta\,[r^*(0)-r_0]}$. Given that awareness increases in social connections and the magnitude of a shock in county, this implies that more depositors are likely to shop around if the counties are more socially connected and the shock is larger.

A larger θ steepens the response of $r^*(m)$, strengthening the feedback from rates to search incentives. Competition therefore magnifies the behavioral response to social-media buzz.

Combining (A5) and (A6), we get the equilibrium deposit rate in county B:

$$r^*(w_{BA}, \lambda, \theta) = \frac{bR + a + \eta\, m^*\big(p(w_{BA}, \Delta r_A), \lambda, \theta\big)}{2b - d}.$$

Comparative statics

Next, we focus on the effects of model parameters on the equilibrium that help us generate empirical predictions.

Proposition 3 (Financial sophistication and competition)**.** *The post-buzz equilibrium deposit rate r^* in county B increases with financial sophistication, and competition. Formally,*

$$\frac{\partial r^*}{\partial \lambda} > 0, \qquad \frac{\partial r^*}{\partial \theta} > 0.$$

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. Greater product substitutability among banks θ increases the elasticity of deposit demand and strengthens the pass-through from depositor activation to equilibrium rates.

Proposition 4 (Buzz spillover)**.** *For any fixed λ and θ,*

$$\frac{\partial r^*}{\partial w_{BA}} > 0, \qquad \frac{\partial r^*}{\partial \Delta r_A} > 0.$$

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 search in connected counties. Higher awareness raises 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, (ii) the share of financially sophisticated depositors, and (iii) the competitiveness of the local banking system.

Appendix B: Additional information on data

Table A1. Summary statistics of deposit rates (Δ: time-difference)

	Small Banks Δr				Large Banks Δr			
Stats	**6m10K**	**12m10K**	**12m100K**	**mm10k**	**6m10K**	**12m10K**	**12m100K**	**mm10k**
N	34,787	34,817	34,745	34,639	21,847	21,837	21,741	20,876
Mean	0.093	0.109	0.111	0.026	0.026	0.023	0.033	-0.001
SD	0.372	0.456	0.470	0.138	0.161	0.201	0.248	0.038
p1	-0.675	-0.886	-0.916	-0.255	-0.340	-0.650	-0.750	-0.080
p50	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
p99	1.848	1.996	2.028	0.700	1.049	1.065	1.200	0.240

Table A2. Summary statistics of SCI-weighted deposit rates time-difference.

	All Areas				Areas>25-miles			
Stats	**6m10K**	**12m10K**	**12m100K**	**mm10k**	**6m10K**	**12m10K**	**12m100K**	**mm10k**
N	35,088	35,088	35,088	35,088	35,088	35,088	35,088	35,088
Mean	0.034	0.040	0.041	0.010	0.028	0.033	0.034	0.009
SD	0.138	0.174	0.178	0.051	0.116	0.146	0.149	0.043
p1	-0.278	-0.399	-0.403	-0.095	-0.230	-0.324	-0.327	-0.082
p50	0.001	0.001	0.001	-0.001	0.000	0.000	0.000	0.000
p99	0.771	0.943	0.966	0.296	0.684	0.827	0.850	0.255

Table A3. Summary statistics of control variables (Δ: time-difference)

Stats	**ΔSBHHI**	**ΔFsophistication**	**ΔRealgdppc**	**ΔPopulation**	**ΔSeniors**	**ΔLBMS**	**LBC**
N	35,088	35,088	35,088	35,088	35,088	35,088	35,088
Mean	0.002	0.101	0.606	0.601	0.004	0.002	0.099
SD	0.020	0.341	4.049	2.172	0.003	0.021	0.298
p1	-0.065	-1.060	-14.320	-1.814	-0.004	-0.083	0.000
p50	0.000	0.099	0.415	0.010	0.004	0.000	0.000
p99	0.097	1.253	19.772	14.741	0.012	0.104	1.000

Table A4. Variable definitions

Variable	Definition
$\Delta r_{c,t}$	Change in county level deposit rates
$\Delta LBMS$	Large banks' market share change
LBC	Dummy that equals one when there is large bank branch closure
SDR	SCI-weighted deposit rate change measure
SLBC	SCI-weighted large banks' branch closures measure
DDR	Distance-weighted (inverse) deposit rate change measure
SBHHI	Herfindahl-Hirschman Index of small banks in the county
HighComp	Dummy equals one when SBHHI time-median is less than 1,800
Realgdppc	County GDP per capita
Seniors	County share of senior population
Population	County population
Fsophistication	Financial sophistication level of population
EP	Industry cosine similarity between counties
EPDR	Economic proximity-weighted deposit rate change

Appendix C: 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.[19]

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.[20] Notably, during the same period no small bank branches were closed in that area. Table A5 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 A5 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 1.07% for nearby branches and 0.88% and 0.83% for faraway branches. Finally, the increase for mm10K deposit rates is 0.20% for nearby and 0.46% for further-away branches. Figure A2 in the Appendix shows the location of the closed *Birmingham* branch and its nearby small

[19] 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.

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

branches, while Figure A5 shows the location of the control group of small bank branches.

Table A5 also reports a univariate pooled-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 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. For money market accounts (mm10k) nearby branches have lower reported rate changes compared to the control group. It is worth noting that *The Grove* branch - the only case without statistical 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. To identify causal effects, we next turn to formal empirical identification tests.

Table A5. 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**	**Δmm10k**
Birmingham	13	10	mean	1.37	1.07	1.07	0.20
			sd	1.71	1.58	1.58	0.36
			t-test	**3.63**	1.38	**1.76**	-3.91
The Grove at 150	6	6	mean	0.48	0.61	0.62	0.48
			sd	0.57	0.69	0.70	0.62
			t-test	-1.44	-1.04	-0.82	0.17
2nd Avenue Drive Up	17	10	mean	1.33	1.11	1.11	0.21
			sd	1.80	1.74	1.74	0.39
			t-test	**4.00**	**2.00**	**2.47**	-4.44
Daniel Building	19	12	mean	1.22	1.05	1.05	0.19
			sd	1.73	1.66	1.66	0.37
			t-test	**3.32**	1.58	**2.08**	-5.24
	Distanced small bank branches (>3 miles)						
Branch name	**No of Branches**	**No of Banks**	Stats	**Δ6m10K**	**Δ12m10K**	**Δ12m100K**	**Δmm10k**
Control	34	18	mean	0.85	0.88	0.83	0.46
			sd	1.34	1.32	1.30	0.62

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 with the help of Chat-GPT. 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 A1 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 A2 is a map of the 13 nearby branches of small banks located within a 3-mile radius of the *Birmingham* branch. Figure A3 is a map of the 17 nearby branches of small banks located within a 3-mile radius of the *Avenue Drive Up* branch. Figure A4 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 A5 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.

Figure A1. *Daniel Building* (former BBVA closed) branch and its nearby small bank branches.

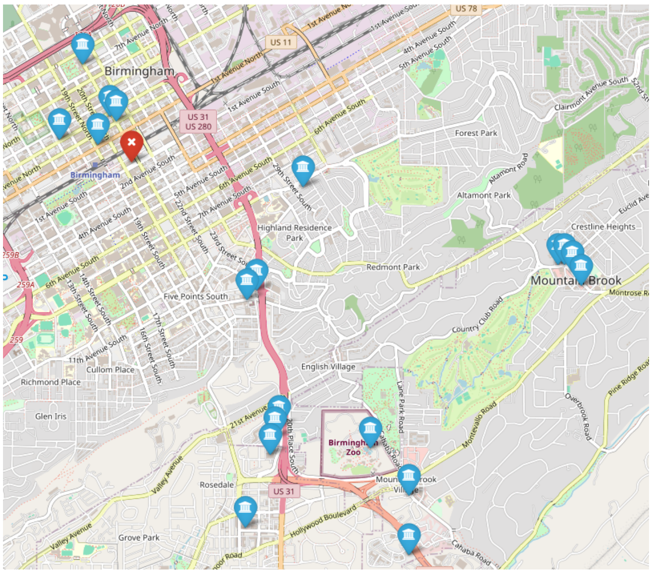


Figure A2. *Birmingham* (former BBVA closed) branch and its nearby small bank branches.

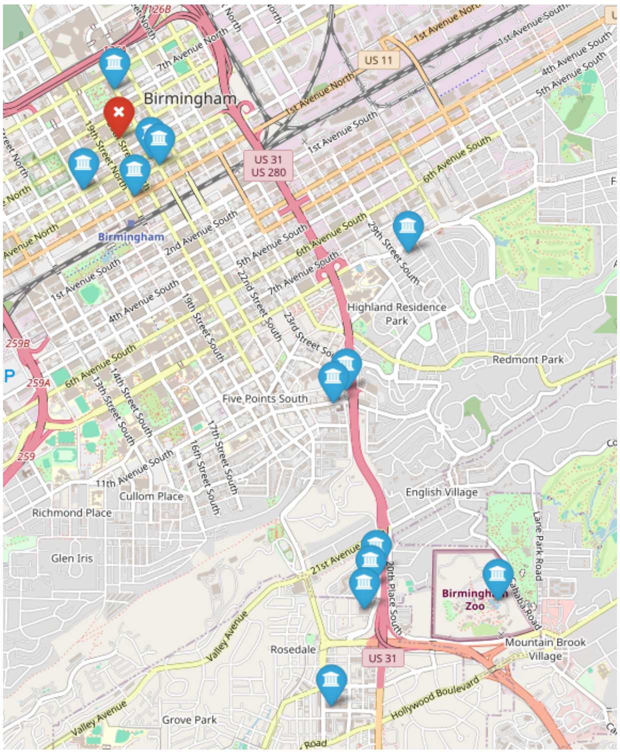


Figure A3. ***Avenue Drive Up*** **(former BBVA closed) branch and its nearby small bank branches.**

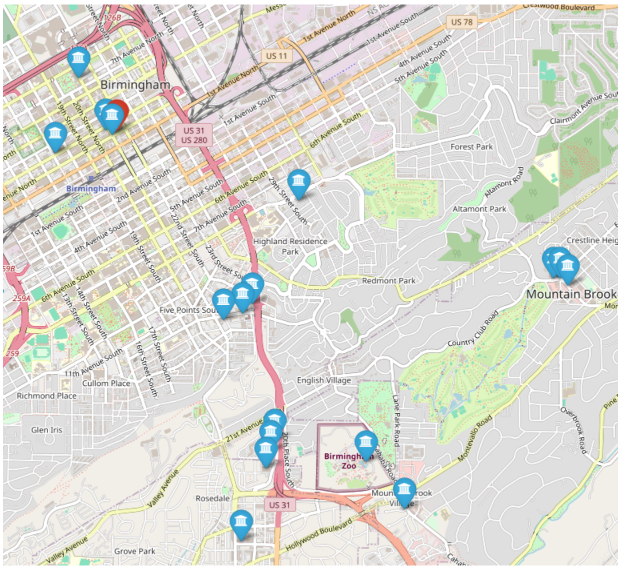


Figure A4. ***The Grove*** **(former BBVA closed) branch and its nearby small bank branches.**

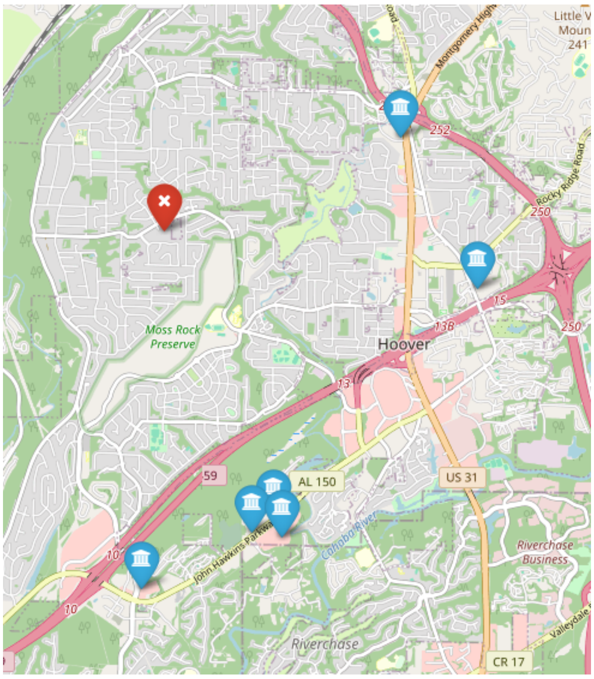
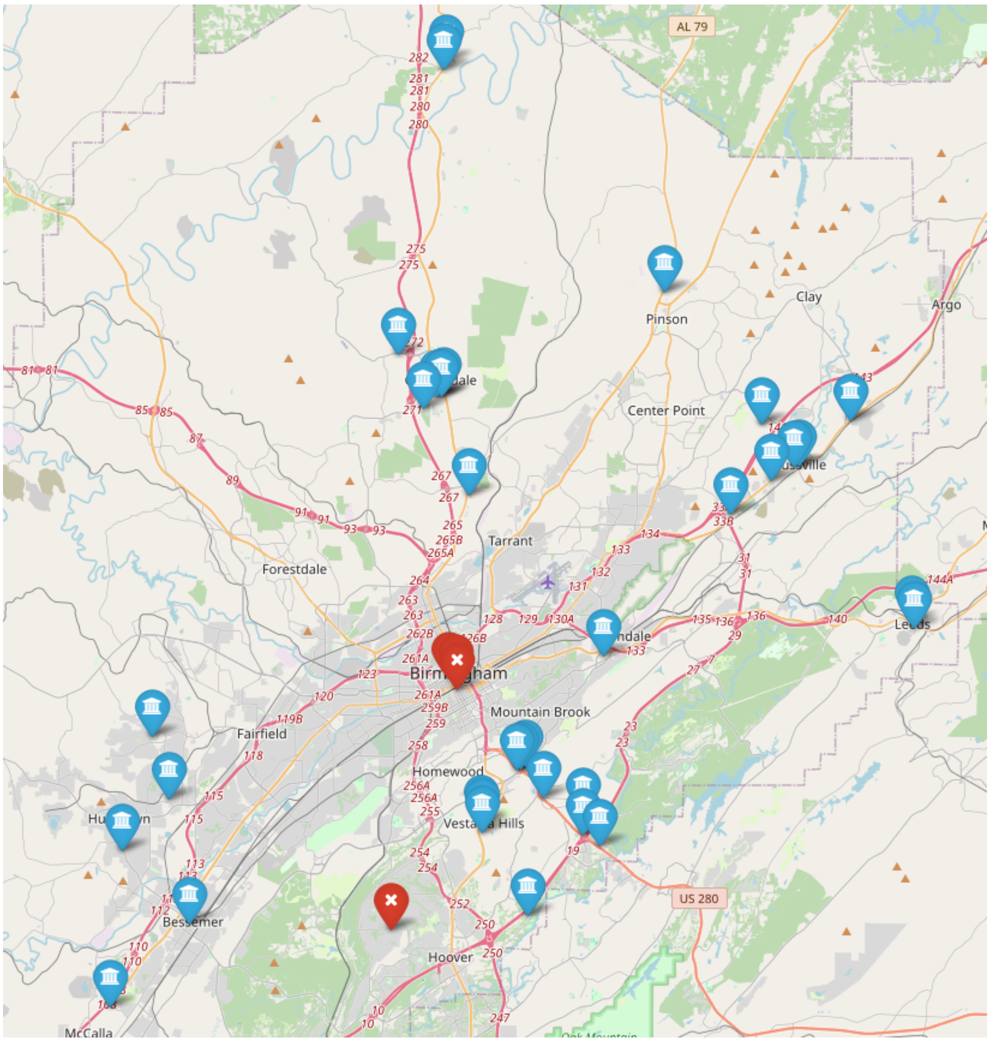


Figure A5. ***The Control*** **group of small bank branches from the same region that are further away from all four former BBVA closed branches.**



Online Appendix

Principal components analysis: Financial sophistication

Populations' financial sophistication is a latent construct that cannot be observed directly. Instead, we rely on observable variables believed to be associated with this latent trait. In our case, we leverage two key data sources at the county level: educational attainment represented by the proportion of the population aged 24 years or older across seven educational categories ("Less than 9th grade", "9th to 12th grade", "no diploma, high school graduate (including equivalency)", "Some college, no degree", "Associate's degree", "Bachelor's degree", "Graduate or professional degree") and stock market participation measured via the fraction of tax returns reporting dividend income and capital gains from the IRS Statistics of Income (SOI).

By construction, these nine variables are highly interrelated and collectively indicative of the underlying financial sophistication of county population. However, including all nine variables directly in subsequent empirical analyses presents several challenges, which Principal Component Analysis (PCA) helps to address.

Figure B1 presents the line plot of the eigenvalues of principal components analysis. The first component has an eigenvalue of 4.56 and explains more than 50% of the common variance (see Table B1). The second and third components have an eigenvalue of 1.57 and 1.06 and explain an additional of 17% and 11.8% of the common variance. The fourth component has an eigenvalue below the threshold of 1 and thus it is not relevant to the analysis.

Table B2 presents the loadings of the components. The first component (Comp1) has negative loadings for the first three education attainment categories ("Less than 9th grade", "9th to 12th grade", "no diploma, high school graduate") and positive loadings for all other variables. In other words, the construct takes higher values in counties with higher proportion of population having a college-level education or above and higher fraction of population reporting dividend income and capital gains in tax returns. These loadings are consistent with the interpretation of first component as the measure of county level financial sophistication. The second component (Comp2) seems to capture middle education levels (College, Associate, HSdiploma) versus both low (Grade8) and high (Graduate) education levels, reflecting education stratification in the middle ranges of attainment. It refers to counties whose residents tend to cluster around middle credentials - high-school diplomas, community-college certificates, and associate's degrees. The third component (Comp3) distinguishes between areas with high rates of basic high school education (HSdiploma) and those with some college education (College). It captures the contrast between areas where educational attainment stalls at high-school versus areas where residents progress into tertiary studies.

Figure B1. Line plot of the eigenvalues of principal components analysis.

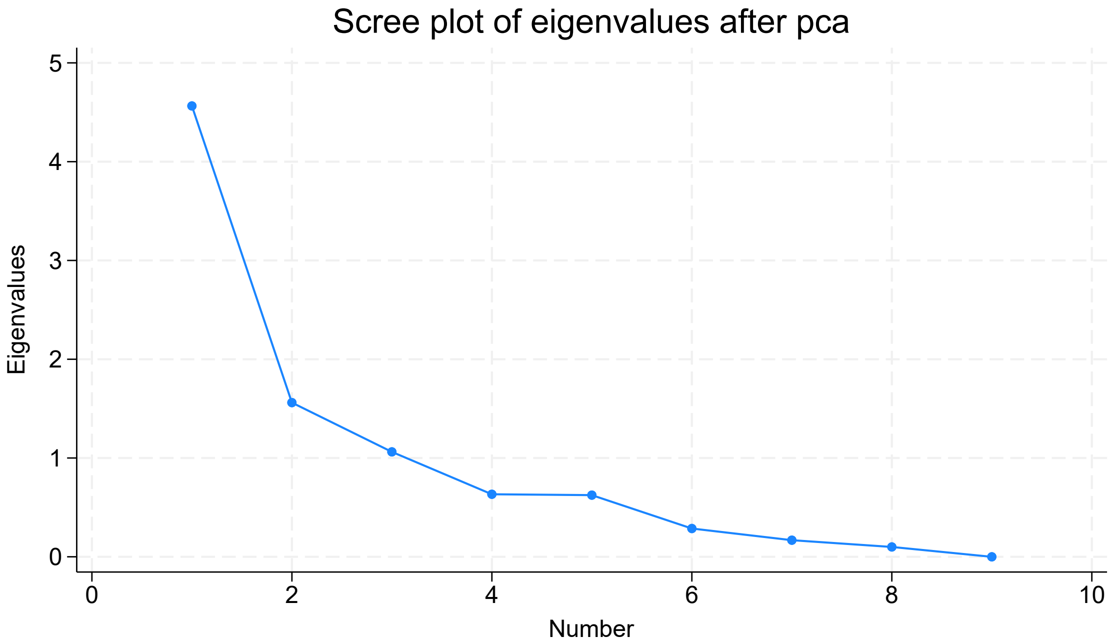


Table B1. Principal components analysis: Top four components

Component	Eigenvalue	Proportion	Cumulative
Comp1	4.564	0.507	0.507
Comp2	1.561	0.173	0.681
Comp3	1.062	0.118	0.799
Comp4	0.633	0.070	0.869

Table B2. Principal components analysis: Top four components loadings

Variable	Comp1	Comp2	Comp3	Comp4
Grade8	-0.296	-0.356	-0.161	0.604
Grade9-12	-0.404	-0.175	-0.083	-0.016
HSdiploma	-0.301	0.327	0.579	-0.266
College	0.112	0.450	-0.694	-0.289
Associate	0.214	0.497	0.003	0.658
Bachelor	0.414	-0.269	-0.084	-0.051
Graduate	0.336	-0.456	-0.020	-0.175
Dividends	0.402	0.001	0.298	0.045
Capgains	0.393	0.076	0.235	0.114

Robustness tests: remove 50-mile proximate counties

Table C1 replicates tests presented in Table 3 after excluding connected counties within the 25-mile radius of the focal county c, while Table C2 includes the replicated tests corresponding to the above Table 4.

Moreover, we repeat the uniform pricing analysis after removing from the calculation of $r^{sc}_{c,t}$ all counties with a distance less than 50miles. The results, presented in Table C3 are economically and statistically equivalent with the results of Table 8.

Table C1. Social connections and small bank deposit rate changes - 50miles radius

The table reports coefficient estimates and robust standard errors (in parentheses) from second stage regressions. In the first stage (see below), the variable *Social Large-bank Branch Closure* is used as an instrument for the *Social Deposit Rate*. The dependent variable is the change in rates of deposits of different sizes and maturities for small banks (6m10K, 12m10k, 12m10k and mm10k). Estimation method is 2SLS with time and county fixed effects. The under-identification F-test is 262.28*** and the robust to clustered errors F statistic for weak identification is 374.73***. The sample period is 2016-2023. The lower part of the table also reports the number of observations. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) 6m10K	(2) 12m10K	(3) 12m100K	(4) mm10k	(5) 6m10K	(6) 12m10K	(7) 12m100K	(8) mm10k
SDR	1.705***	1.602***	1.542***	1.899***	1.616***	1.571***	1.524***	1.712***
	(0.243)	(0.255)	(0.262)	(0.238)	(0.223)	(0.230)	(0.236)	(0.217)
SDR × *HighComp*					0.551	0.190	0.111	1.171**
					(0.472)	(0.412)	(0.415)	(0.564)
SBHHI	0.141	0.088	0.016	0.002	0.135	0.086	0.014	-0.004
	(0.142)	(0.171)	(0.176)	(0.057)	(0.142)	(0.171)	(0.177)	(0.057)
Seniors	0.620	-0.936	-1.040	0.062	0.359	-1.033	-1.096	-0.140
	(1.222)	(1.402)	(1.441)	(0.512)	(1.220)	(1.396)	(1.438)	(0.522)
Population	0.008	-0.004	-0.002	0.006**	0.006	-0.004	-0.002	0.005**
	(0.006)	(0.008)	(0.008)	(0.003)	(0.006)	(0.008)	(0.008)	(0.003)
Realgdppc	0.001	0.001	0.001	0.000*	0.001	0.001	0.001	0.001**
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
FSophistication	0.020**	0.020*	0.019*	-0.001	0.021**	0.020*	0.019*	-0.000
	(0.009)	(0.011)	(0.011)	(0.004)	(0.009)	(0.011)	(0.011)	(0.004)
Obs.	17,162	17,191	17,152	17,055	17,162	17,191	17,152	17,055

Table C2. Social connections, small bank deposit rate changes and financial sophistication - 50miles radius

The table reports coefficient estimates and robust standard errors (in parentheses) from second stage regressions. In the first stage (see below), the variable *Social Large-bank Branch Closure* is used as an instrument for the *Social Deposit Rate*. The dependent variable is the change in rates of deposits of different sizes and maturities for small banks (6m10K, 12m10k, 12m10k and mm10k). Estimation method is 2SLS with time and county fixed effects. The under-identification F-test is 216.53*** and the robust to clustered errors F statistic for weak identification is 109.98***. The sample period is 2016-2023. The lower part of the table also reports the number of observations. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) 6m10K	(2) 12m10K	(3) 12m100K	(4) mm10k
SDR	1.720***	1.093**	1.155**	1.963***
	(0.529)	(0.531)	(0.542)	(0.567)
SDR × *HighComp*				
SDR × *HighSoph*	-0.014	0.471	0.359	-0.061
	(0.397)	(0.365)	(0.370)	(0.489)
SBHHI	0.141	0.079	0.009	0.003
	(0.142)	(0.173)	(0.177)	(0.057)
Seniors	0.633	-1.454	-1.434	0.084
	(1.269)	(1.486)	(1.518)	(0.534)
Population	0.008	-0.004	-0.002	0.006**
	(0.006)	(0.008)	(0.008)	(0.003)
Realgdppc	0.001	0.001	0.001	0.000*
	(0.001)	(0.001)	(0.001)	(0.000)
FSophistication	0.020**	0.024**	0.022*	-0.001
	(0.010)	(0.012)	(0.012)	(0.004)
Obs.	17,162	17,191	17,152	17,055

Table C3. Use of social media and small banks uniform pricing - 50miles radius

The table reports coefficient estimates and robust standard errors (in parentheses) from difference-in-difference regressions. The dependent variable is the change in the distance between (small banks) rates of deposits of different sizes and maturities (6m10K, 12m10k, 12m10k and mm10k) and the weighted average of deposit rates of social peers. Estimation method is OLS with time and county fixed effects. The data frequency is quarterly and the sample period is 2011q2-2023q3. The lower part of the table also reports the number of observations. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) 6m10K	(2) 12m10K	(3) 12m100K	(4) mm10k	(5) 6m10K	(6) 12m10K	(7) 12m100K	(8) mm10k
$SC \times (r_{c,t-1} - r^{sc}_{c,t-1})$	-0.002***	-0.002***	-0.002***	-0.000	-0.001***	-0.001**	-0.001**	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
$SC \times (r_{c,t-1} - r^{sc}_{c,t-1}) \times HighComp$					-0.008***	-0.009***	-0.005**	-0.004***
					(0.002)	(0.002)	(0.002)	(0.002)
$(r_{c,t-1} - r^{sc}_{c,t-1})$	-0.076***	-0.098***	-0.076***	-0.110***	-0.091***	-0.109***	-0.091***	-0.115***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)
$(r_{c,t-1} - r^{sc}_{c,t-1}) \times HighComp$					0.054***	0.048***	0.045***	0.021***
					(0.010)	(0.010)	(0.009)	(0.008)
SC	0.002***	0.002***	0.002***	0.001***	0.002***	0.002***	0.002***	0.001***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
$SC \times HighComp$					0.004***	0.003***	0.003***	0.002***
					(0.001)	(0.001)	(0.001)	(0.000)
$SBHHI$	-0.014**	-0.015*	-0.018**	-0.004	-0.013**	-0.014*	-0.017**	-0.003
	(0.007)	(0.009)	(0.009)	(0.003)	(0.007)	(0.009)	(0.009)	(0.003)
$Seniors$	-0.236***	-0.239***	-0.243***	-0.071***	-0.226***	-0.232***	-0.234***	-0.066***
	(0.044)	(0.052)	(0.054)	(0.020)	(0.044)	(0.052)	(0.054)	(0.020)
$Population$	0.013	0.021**	0.023**	0.020***	0.009	0.018*	0.020**	0.018***
	(0.008)	(0.009)	(0.010)	(0.004)	(0.008)	(0.010)	(0.010)	(0.004)
$Realgdppc$	-0.000	-0.000	0.000	0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$FSophistication$	0.000	-0.001	-0.002	-0.000	0.000	-0.001	-0.002	-0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Constant	-0.010	-0.040	-0.044	-0.062***	-0.003	-0.034	-0.039	-0.058***
	(0.031)	(0.037)	(0.038)	(0.015)	(0.031)	(0.037)	(0.038)	(0.015)
Obs.	143,461	143,555	144,811	142,890	143,461	143,555	144,811	142,890

First-Stage results

Table C4. First-Stage results
The table reports coefficient estimates and robust standard errors (in parentheses) from difference-in-difference first stage regressions. The dependent variable is $\Delta LBMS$ for column (1) and the *Social Deposit Rates* of different sizes and maturities for small banks (6m10K, 12m10k, 12m10k and mm10k) for columns (2)-(5). The sample period is 2012-2023 for column (1) and 2016-2023 for columns (2)-(5). The lower part of the table also reports the number of observations. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) $\Delta LBMS$	(2) SDR(6m10K)	(3) SDR(12m10K)	(4) SDR(12m100K)	(5) SDR(mm10k)
LBC	0.020*** (0.001)				
SLBC		0.806*** (0.076)	1.053*** (0.109)	1.077*** (0.112)	0.355*** (0.034)
DDR		0.056*** (0.003)	0.042*** (0.004)	0.042*** (0.004)	0.070*** (0.004)
SBHHI	-0.040*** (0.015)	0.119*** (0.036)	0.156** (0.066)	0.158** (0.068)	0.044** (0.020)
Seniors	-0.011 (0.047)	-1.175** (0.583)	-1.534** (0.781)	-1.548* (0.798)	-0.398* (0.236)
Population	0.000 (0.000)	-0.000 (0.001)	-0.011*** (0.003)	-0.011*** (0.003)	-0.004*** (0.001)
Realgdppc	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)	0.017*** (0.003)	0.014*** (0.005)	0.013*** (0.005)	0.005*** (0.001)
Constant	0.001*** (0.000)	-0.002 (0.004)	0.028*** (0.006)	0.029*** (0.006)	-0.002 (0.002)
Obs.	29,616	23,392	17,326	17,326	17,326

Table C5. First-Stage results for geographic proximity tests

The table reports coefficient estimates and robust standard errors (in parentheses) from difference-in-difference first stage regressions after removing the 25-mile proximate counties (columns 1-4) and the 50-mile proximate counties (columns 5-8). The dependent variable is the *Social Deposit Rates* of different sizes and maturities for small banks (6m10K, 12m10k, 12m10k and mm10k). The sample period is 2016-2023. The lower part of the table also reports the number of observations. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) 6m10K	(2) 12m10K	(3) 12m100K	(4) mm10k	(5) 6m10K	(6) 12m10K	(7) 12m100K	(8) mm10k
SLBC	1.555***	1.697***	1.717***	0.579***	3.273***	3.648***	3.685***	1.201***
	(0.120)	(0.145)	(0.150)	(0.044)	(0.169)	(0.215)	(0.219)	(0.065)
SBHHI	0.098**	0.131**	0.136**	0.035*	0.063**	0.083**	0.086**	0.025**
	(0.046)	(0.058)	(0.060)	(0.018)	(0.028)	(0.036)	(0.036)	(0.011)
Seniors	-0.786	-1.145*	-1.149	-0.317	-0.689**	-0.984**	-0.975**	-0.256**
	(0.563)	(0.694)	(0.712)	(0.217)	(0.337)	(0.426)	(0.434)	(0.130)
Population	-0.004**	-0.006**	-0.006**	-0.001*	-0.002*	-0.003**	-0.003**	-0.001
	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Realgdppc	0.001**	0.001*	0.001*	0.000**	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	0.010***	0.012***	0.012***	0.004***	0.005**	0.005**	0.005**	0.002**
	(0.003)	(0.004)	(0.004)	(0.001)	(0.002)	(0.003)	(0.003)	(0.001)
Constant	0.046***	0.059***	0.060***	0.015***	0.015***	0.022***	0.022***	0.004***
	(0.003)	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
Obs.	17,326	17,326	17,326	17,326	17,326	17,326	17,326	17,326

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