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

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Abstract

We examine how online social networks among bank customers impact banks' deposit-pricing behavior. We begin by documenting that small banks compete primarily on price and adjust their rates in response changes in market conditions after a closure of a large bank branch. Using county-level online social connection data and a two-stage regression framework, we find that they do so even following deposit rate shocks in socially connected but geographically distant areas. The effect is strong and persistent and is not driven by geographic proximity or economic linkages. Our results also indicate that social spillovers are amplified in banking markets characterized by high competition and by customers with greater financial sophistication. A corollary of our findings, also tested here, is that increased social connectedness accelerates rate convergence of small banks across connected counties.

Keywords: Social connections, social proximity to deposit rates, deposit pricing, information transmission, uniform pricing

JEL classification: G20; G21; G23; G29

*The views expressed in this paper are those of the authors and may not necessarily represent those of the European Central Bank, or the Eurosystem.

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1 Introduction

An extensive literature on deposit rate-setting has explored the determinants influencing the distribution of deposit rates within and across banks. Earlier studies argue that market power, derived from concentrated market shares, explains the different deposit-pricing behavior of large and small banks (Sharpe 1997, Calem & Nakamura 1998, Drechsler, Savov & Schnabl 2017). Recent studies challenge this idea, suggesting that large banks predominantly use uniform deposit rate-setting policies, largely ignoring local market concentration (Granja & Paixao 2023, Begenau & Stafford 2023, d'Avernas, Eisfeldt, Huang, Stanton & Wallace 2023). At the same time, however, advancements in technology broaden the geographic scope of competition and raise questions about the relevance of traditional local concentration measures in capturing pricing power.

In this paper, we explore a new determinant of local deposit rates and pricing power: online social networks. While the existing empirical research has highlighted online social network effects as an important driver of consumers' decision making (Kuchler, Li, Peng, Stroebel & Zhou 2022), the question of how these networks influence the distribution of deposit rates remains largely understudied. Social interactions have increasingly moved to digital social media platforms, altering how financial information is produced, distributed and consumed (Cookson, Mullins & Niessner 2024). Interactions through social media platforms act as a new channel, producing novel, value-relevant information for consumers (Cao, Zhang, Feng & Meng 2021). Hirshleifer, Peng & Wang (2024) study the effects of social connectedness on information transmission and return and volume dynamics. Flynn & Wang (2022) show that social connections transmit shocks related to natural disasters that influence banks' deposit flows. In a complementary study, Zhou (2025) shows that social networks play an important role in making Fintech lending more attractive to uninformed customers.

We provide novel evidence on the relationship between households' online social connections and deposit pricing of small banks. To do so, we exploit the exposure (through social networks) of small banks in an area to changes in the banking market structure in a socially connected area. This approach aligns with recent applications of quasi-experimental shift-share designs (e.g., Bartik instruments in labor and housing markets) the validity of which hinge on the exogeneity of shocks, a condition our setting satisfies given the localized, idiosyncratic nature of market structure changes in socially connected counties. It stands to reason that banks' decisions about pricing are affected by the interactions of consumers with their peers. To the extent that this peer influence is strong, the effect of a local market concentration change on deposit rates will be further amplified. Thus, our identification strategy provides causal estimates of the spillover of deposit price changes across US county-level social networks.

Our analysis starts by documenting empirically how a large bank exit induces local small banks to adjust their deposit rates in response to the changed competitive landscape. For this, we adopt an instrumental variable two-step approach where in the first step, we use a dummy for a large bank branch closure in a county as an instrument for the market share loss of large banks in that county. To capture exogenous changes in the competitiveness of local banking markets, we focus on branch closures of large banks that have been involved in a merge within a window of two years (Garmaise & Moskowitz 2006). In the second step, we estimate the impact on the changes of deposit rates for large and small banks. Using this empirical strategy, we confirm previous findings about the heterogeneity in deposit pricing between large and small banks: the impact is positive and significant only for the deposit rates offered by small banks supporting our hypothesis that small banks react to local market competition characteristics while large banks follow a uniform pricing strategy. Consistent with our prediction that small banks compete on price, our findings also suggest that the effect is pronounced in markets where competition between small banks is high.

We then exploit this variation to examine how deposit rate changes in one market affect rates in socially connected "peer areas". To examine these relationships, we measure social connectedness between US counties using the Social Connectedness Index (SCI, Bailey, Cao, Kuchler & Stroebel (2018)). This measure is based on aggregated and anonymized Facebook friendship links between counties. Facebook's scale and the relative representativeness of its user body make the SCI a useful proxy for real-world social connections (see, for example, Bailey, Cao, Kuchler, Stroebel & Wong (2018)). By combining this measure with branch-level deposit rate data from RateWatch and information on the quantity of deposits at the branch level from the Summary of Deposits (SOD) dataset collected by FDIC, we construct measures of *social proximity to deposit rate changes* and *social proximity to market share changes* following large bank exits to investigate whether and how social connections between fips codes influence banks' pricing strategies and depositor behavior.

The causal inference faces one major challenge arising from the existence of unobserved common factors that drive deposit rates to change simultaneously in multiple markets without network spillovers. In order to isolate the role of social networks, as opposed to factors related to unobserved common characteristics, preferences, or exposures, we again adopt a two-step approach. In the first step, we use as an instrument for the social proximity to deposit rate changes, the change in the local market share of large banks in all socially connected areas. This decision is based on our earlier findings that small banks compete on deposit prices, following changes in the market share of large banks. In the second step, we estimate the impact of socially connected rates' change on the deposit rates of banks in the focal area. We control for county and year fixed effects and a number of time-varying characteristics of the focal area, including local concentration measures for small banks, to address further the concern of endogeneity. We also control for the physical distance between the focal and deposit-rate-affected counties using a distance-weighted measure of exposure to deposit rate shocks. We find evidence in support of our hypothesis. Deposit rates of small banks in a focal area increase after an increase in the socially connected deposit rates driven by changes in their local market structure. Consistent with our earlier prediction of the key role of local bank concentration, our findings also suggest that the social spillover effect is more pronounced in markets where competition between small banks is high.

While our analysis does not allow to distinguish between all possible explanations why social connections might influence deposit pricing decisions of banks, we conduct several exercises to reinforce the social connections mechanism. First, we offer more evidence that our measure is not confounded by geographic proximity by excluding all counties within 25 and 50-mile radius from the focal county. We also show that our findings are not driven by cross-country economic linkages (Flynn & Wang 2022). Third, we ensure that our social connections are "active" accounts by controlling for a more refined measure of indirect exposure to deposit rate shocks which takes into account social connections only when counties have a high penetration of residential broadband internet. Finally, we draw from recent literature which argues that proxies for financial sophistication are another source of market power for banks beyond concentration, see for example Drechsler et al. 2017, Fleckenstein & Longstaff 2024, as well as from the literature which argues that there is a link between financial and digital sophistication of individuals (Gambacorta, Gambacorta & Mihet 2023). We expect customers with high financial sophistication to be more engaged in social networks. At the same time, we expect small banks in markets with a high financial sophistication level to have less market power and thus be more responsive to deposit rate changes in socially connected areas.

Financial sophistication is measured by combining two population characteristics: educational attainment and stock market participation. We apply Principal Component Analysis (PCA) to estimate a financial sophistication proxy from nine correlated county-level variables related to educational attainment and stock market participation. When splitting the sample into high vs low sophistication, we find strong evidence that small banks in a focal area increase their deposit rates after an increase in deposit rates in socially connected areas, only for the highly sophisticated subsample. This provides a novel link between bank deposit pricing behavior, financial sophistication as an additional source of market power, and social networks.

A corollary of these findings is that, as participation to social networks increases, the social linkages should lead to greater uniformity in small banks' deposit rates. Specifically, increased social interactions will effectively diminish local market heterogeneity and prompt small banks to adjust towards a common equilibrium rate. In the final part of the paper, we employ a β-convergence type model (Barro & Sala-i Martin 1992) to test whether initial gaps between a county's deposit rates and the weighted average of deposit rates of its socially connected peers shrink over time. A negative and statistically significant β in the Differences-in-Differences empirical specification indicates clear evidence of convergence in deposit rates across banks and across counties. More interestingly, we find that social connectivity increases the speed of adjustment towards convergence to a common rate only for the small bank.

Relation to the literature. The results of this paper provide, to the best of our knowledge, the first empirical evidence that social networks impact the bank deposit rates through local market concentration changes and our analysis provides several contributions to the literature. First, the paper contributes to the literature on uniform deposit pricing of banks. Recent studies demonstrate that while large banks tend to set uniform rates across extensive regions, smaller banks base their rates on local competitive conditions. d'Avernas et al. (2023) empirically show that large banks experience significantly lower demand elasticities with respect to deposit rates, and they are more likely to be located in markets with less deposit-rate-elastic customers. Begenau & Stafford (2023) highlight that large banks have a near universal use of uniform deposit rate setting policies across large geographies. Granja & Paixao (2023) show that US banks price deposits almost uniformly across their branches and that this pricing practice is crucial to explain the deposit rate dynamics following bank mergers. This paper presents further evidence on the (no) responsiveness of (large) small banks to an exogenous shock to local market concentration.

The paper also adds to the growing body of work 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 models and empirical evidence suggest that direct social interactions play important roles in economic decision making (e.g., Hong, Kubik & Stein 2004, Shiller 2019, Hirshleifer 2020). The literature has provided extensive evidence of the social network effect on home purchases (Bailey, Cao, Kuchler & Stroebel 2018), leverage choices (Bailey, Dávila, Kuchler & Stroebel 2019) and product adoption (Bailey, Johnston, Kuchler, Stroebel & Wong 2022). The paper more close to ours is by Kuchler et al. (2022), who examine the impact of an area's social proximity to equity capital provided by US mutual funds on stock liquidity and firm valuation. We provide novel evidence on how social networks affect bank competition and pricing strategies.

Finally, we add to a nascent literature on the effects of online social connections on banks. Flynn & Wang (2022) find that counties experience an increase in bank deposits when they are more socially connected to counties affected by natural disasters. Rehbein & Rother (2025) show that cross-county bank lending increases with social connectedness. Also, Zhou (2025) examine the role of social networks in Fintech lending adoption and refinancing. We explore a complementary channel examining the impact of an area's social proximity to bank deposit pricing setting through changes in pricing power.

The remainder of the paper is structured as follows. In Section 2 we describe the data. Section 3 explains the empirical setup and presents the results for testing deposit pricing behavior of small vs large banks following a change in local market concentration. Section 4 focuses on the online social network spillover effect. Section 5 provides evidence on the role of online social connectedness on the speed of convergence towards a common deposit rate across socially connected counties. Section 6 concludes.

2 Data and social connectedness

We compile bank and economic data at the county 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.[1] We focus on the brick and mortar branches only, excluding deposits and rates of online banks listed in Erel, Liebersohn, Yannelis & Earnest

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

(2023). Online banks operate beyond any local market and thus 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 A2 in the Appendix report summary statistics for the deposit rates and for the main control variables in the form (time-differences) used in the empirical analysis.

2.1 Branch-level bank data

Our main dataset consists of branch-level deposit rates from RateWatch. RateWatch surveys over 100,000 bank branches and collects weekly advertised deposit rates and annual percentage yield (APY) on new accounts. Our sample comprises all branches of commercial banks and savings & loans institutions with a valid Federal Deposit Insurance Corporation (FDIC) identifier that report to RateWatch. In particular, we follow Begenau & Stafford (2023) and include in our sample "rate setter" branches as well as "follower" branches - branches whose deposit rates are determined by a centralized rate-setting policy. Our choice to include all branches is backed by the fact that focusing on "rate setter" branches only would eliminate over 90% of all US commercial bank branches (Begenau & Stafford 2023). Furthermore, including "follower" branches, many of them being branches of large banks, is consistent with our theoretical argument that large banks are primarily using uniform price setting and therefore, local competition should matter for small bank deposit rates only.

RateWatch collects deposit rates for a large portfolio of standardized deposit products such as checking accounts, savings products, and certificates of deposits (CDs) of different sizes and maturities. We focus our analysis on one of the most common products: the 12-month CD with a minimum account size of \$10,000 (*12MCD10K*). However, we also report results from three additional deposit products that have different terms to test if our results hold only for specific types, maturities and amounts. Thus, we focus on the 6-month CD with a minimum account size of \$10,000 (*6MCD10K*), the 12-month CD with a minimum account size of \$100,000 (*12MCD100K*) and the money market accounts (MMs) with a minimum account size of \$10,000 (*mm10k*). We keep the rate quotes from the last month of a given quarter to construct a quarterly dataset.

RateWatch also contains information on the FDIC branch identifier and of the financial institution that owns the branch. We use this identifier to complement the branch-level deposit rate data with branch-level data on total branch deposit amounts, the Summary of Deposits (SoD) dataset. This is an annual survey, conducted as of June 30, that collects information about the deposits held in branch offices of all FDIC-insured institutions, including insured US branches of foreign banks.[2] It provides a comprehensive listing of branch office locations and total deposits reported by these branches. Based on the assets reported in SoD, we classify banks as large if the total amount of assets exceeds 100 billion.[3] We use these data to calculate the deposit concentration (Herfindahl-Hirschman index, HHI) of small banks in a county deposit market (*SBHHI*) as well as the change in the (deposit) market share of large banks (*LBMS*).

Finally, we download branch closure data from FDIC and bank merger activity from the Federal Financial Institutions Examination Council (FFIEC).

2.2 County-level social connectedness

To measure the intensity of social connectedness between two counties, we use the Social Connection Index (SCI) provided by Facebook and first introduced by Bailey, Cao, Kuchler & Stroebel (2018). It is defined as the number of cross-county Facebook friendship links divided by the product of county-pair populations:

$$Social\ connectedness_{i,j} = \frac{number\ of\ friendship\ links_{i,j}}{population_i \times population_j} \tag{1}$$

[2] To align quarterly deposit rates with the annually updated SoD, published each June, we pair the SoD of year t with the previous four quarters, i.e., the q1-q2 of year t and q3-q4 of year $t-1$.

[3] According to FED, large banking organizations (LBOs) are domestic financial institutions with total consolidated assets of at least \$100 billion. https://www.federalreserve.gov/supervisionreg/topics/large-banking-organization-supervision.htm

The SCI data available to us is equal to the original Social Connectedness value of the county pair divided by the maximum Social Connectedness value in the dataset, and then multiplied by 1 billion. Therefore, the SCI data lie between 1 and 1 billion, and before using the data in our study, we divide the SCI value by 1 billion in order to convert it into a weight.[4] Hence, the variable quantifies the relative probability that a person in county i is acquainted with a person in county j. A growing literature has made use of the data to study, for example, 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). Note that the SCI is constructed using the snapshot of Facebook connections at August 2020. Because Facebook is mostly used to connect with friends and family in real life, the SCI captures persistent social connections and is largely stable over time (Flynn & Wang 2022).

2.3 County-level characteristics

Bank's local markets are defined the counties where the bank has branches and we include all US counties from all states except Alaska and Connecticut.[5] The county-level population data are from the Surveillance, Epidemiology, and End Results (SEER) Program.[6] We control for total population of the county (*Population*). Moreover, demographic variation in savings behavior affects bank deposit local markets (Becker 2007) therefore, we control for the proportion of population above 65 years old (*Seniors*). Supply of deposits is also positively correlated to local economic activity, Therefore, we also control for real GDP (i.e. county GDP adjusted to remove the effects of inflation over time) from the Bureau of Economic Analysis divided by total population (*Realgdppc*). Finally, we use the NBER

[4] See the methodology description at https://dataforgood.facebook.com/dfg/docs/methodology-social-connectedness-index for more details.

[5] Over our sample period, Alaska had many redraws of local "boroughs", the geographical equivalent to a county, that makes calculating time-consistent local characteristics infeasible. Similarly, in 2022, the U.S. Census Bureau adopted nine new planning regions as county-equivalents replacing Connecticut's eight counties used historically.

[6] The data can be downloaded from https://seer.cancer.gov/popdata/yr1969_2020.19ages/us.1969_2023.20ages.adjusted.txt

County Distance Database for the geographic distance between counties using the Haversine formula based on internal points in the geographic area.

Another local demographic that interacts with banks' deposit market power is customers' financial sophistication (Drechsler et al. 2017). We measure financial sophistication (*Fsophistication*) combining two population characteristics: educational attainment and stock market participation. Specifically, we draw the Census Bureau data table of educational attainment from American Community Survey. County-level education data contains the proportion of the local population aged 24 years or older distributed to 7 different groups: "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". Furthermore, to measure stock market participation of the local population, we use county level data from the IRS Statistics of Income (SOI) on Individual Income Tax Returns and specifically the fractions of tax returns reporting dividend income and capital gains.

Then, we apply Principal Component Analysis (PCA) to estimate financial sophistication (*Fsophistication*) from the nine correlated county-level variables - seven educational attainment categories and two measures of stock market participation. This method provides a data-driven, parsimonious measure of financial sophistication that captures the largest shared variance among the seven educational attainment and two stock market participation measures. Unlike including all nine variables separately, which would risk multicollinearity and interpretational complexity, PCA constructs an orthogonal index that efficiently summarizes the latent construct of financial sophistication while mitigating noise and idiosyncratic variation. This parsimonious approach allows for clearer empirical inference and a more robust measure of the underlying trait, enhancing both statistical efficiency and interpretability. The first component explains more than 50% of the common variance and has negative loadings for the first three education attainment categories and positive loadings for all other variables, consistent with the interpretation of this variable as the measure of county-level financial sophistication. We offer more information about the derivation of the financial sophistication proxy using PCA in the Appendix B.

3 Local market competition and deposit rates

This section provides motivating empirical evidence on the different behavior in terms of deposit pricing of large compared to small banks. There is a growing literature on uniform rate setting in banking by large banks. For example, in a recent paper, d'Avernas et al. (2023) show that large-bank customers receive lower rates on average and are less rate-sensitive since they have a higher willingness to pay for superior liquidity services - as, for example, larger branch and ATM networks, customized online banking, or a broad array of financial services - provided by large banks. Thus, across markets, large banks offer lower rates because of the lower average elasticity of the depositors in the markets they serve. Within markets with both large and small banks, small banks pay higher rates than large banks in order to attract depositors without offering superior liquidity services. Put it differently, large banks compete on services offered while small banks compete on price. What follows offers empirical tests to support these conjectures.

3.1 Empirical specification

Assume a focal area c at time t, where several local single-market small banks operate offering deposit rates r_c while a large multi-market bank with branches in this county offers uniform deposit prices r. Now assume that the large bank decides to close its branch(es) in the county after the large bank merges with another bank, as part of a restructuring of the new bank's branch network. This decision causes a change in the competitiveness of the local banking market that is independent of the underlying characteristics of the local market.

In this setup, we would expect small banks in county c to respond to the large bank branch closure by increasing their deposit rates. The reason is that when a large bank closes a branch, this induces small banks to compete on price to attract the unserviced customers of the closed large bank branch. Large banks, on the other hand, compete on services offered, and thus we would expect them to keep the uniform rate offered across all regions constant.

To test this hypothesis, we use a two-stage least squares (2SLS) IV regression setup where in the first step the large bank branch closure serves as an exogenous variable to estimate the associated change in large banks' market share. The first stage regression is:

$$\Delta LBMS_{c,t} = \alpha + \alpha_1 BC_{c,t} + \alpha_2 \Delta x_{c,t} + f_c + f_t + \epsilon_{c,t} \tag{2}$$

where $\Delta LBMS_{c,t}$ is the change in the market share of large banks in county c following the closure of a branch, $BC_{c,t}$ is a dummy that equals one if there a branch closure and $x_{c,t}$ is a set of control variables in first differences. Because branch closures may be confounded with several other local measures and characteristics, we focus on branch closures of large banks that have been involved in a merge 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). We control for small banks' market concentration HHI (*SBHHI*), 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_c and f_t, ensuring that identification comes from within-unit deviation in rates $\Delta r_{c,t}$ from pre- and post- branch closure trends. Finally, $\epsilon_{c,t}$ is the error term adjusted for within-county correlation.

Then, the second stage regression is the following:

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

where $\Delta r_{c,t}$ is the independent variable of interest, i.e. the change in rates of deposits of different sizes and maturities of either large or small banks.

We further anticipate that local competition measures play a role and 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 a dummy (*HighComp)* which equals one when the county's time-median HHI index of the small banks is lower than 1,400.[7]

3.2 Panel regression estimates

Our deposit rate data is quarterly but the local market competition, $\Delta LBMS$, is observed only annually. Thus, we define year as the time variable and we calculate differences based on the variables' year-end values. Our final sample is a county-year panel dataset covering the period from 2012 through 2023. To avoid any confounding effects, we exclude from the sample counties with small bank branch closures taking place at the same year with the large bank branch closures.

Table 1 and Table 2 present the estimated effect using the second stage regression in eq. 3 where we test for the effect of changes in local bank concentration due to a branch closure on the deposit rates of small and large banks respectively. First stage regression results, where merger-induced large bank branch closures are used as an instrument for the change in the market share of large banks, are not reported for brevity.

We find support for our first hypothesis that small banks increase their deposit rates after a large bank decides to close a branch in the county, as shown by the significant positive coefficients of *LBMS* in columns (1)-(4) in Table 1. For example, the loss of market share from the large bank branch closure raises the 12m-CD10K rate by 0.822 basis points. The effect is lower in magnitude, but still significant, for the mm10k because the rates in money

[7] According to Department of Justice guidelines referred to mergers, markets with HHI between 1,000 and 1,800 as "moderately concentrated" and above 1,800 as "highly concentrated". The threshold of 1,400 used here splits the moderately concentrated into two group, incorporating the moderately concentrated local markets with the lowest 50% HHI (1,000-1,400) to competitive markers and the moderately concentrated local markets with the highest 50% HHI (1,400-1,800) to non-competitive markers.

market accounts are lower than those in certificates of deposits.

Columns (5)-(8) provide further evidence about the competition channel: when local competition (concentration) between small banks is high (low), then we observe an increase in the deposit rates. On the other hand, when local competition between small banks is low, then we observe no increase in small banks deposit rates as the main effects are statistically insignificant.

Finally, consistent with the uniform pricing strategy, Table 2 shows that large banks, in general, do not in general react to local market competition changes and continue to offer uniform pricing.

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, merger-induced large bank branch closures are used as an instrument for the change in the market share of large banks (*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 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
LBMS	0.851***	0.822**	0.900**	0.351***	0.173	0.157	0.313	0.134
	(0.321)	(0.373)	(0.385)	(0.128)	(0.280)	(0.333)	(0.343)	(0.112)
LBMS × *HighComp*					3.328***	3.269**	2.870**	1.057**
					(1.246)	(1.403)	(1.445)	(0.485)
SBHHI	0.100	0.118	0.084	0.013	0.019	0.038	0.015	-0.013
	(0.099)	(0.119)	(0.122)	(0.042)	(0.102)	(0.123)	(0.126)	(0.042)
Seniors	1.723**	0.085	0.151	0.471	1.726**	0.087	0.156	0.472
	(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)	(0.003)	(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, merger-induced large bank branch closures are used as an instrument for the change in 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 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
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

4 Social connectedness and deposit rates

In this section, we turn to our main research question on whether there are social spillovers in bank deposit pricing. The empirical estimates of the previous section inform the identification strategy for testing for the social network effects.

We expand the example from the previous section by assuming that in some counties a, b that are geographically distant from our focal area c, small banks offer different deposit rates r_a and r_b respectively. Moreover, the large multi-market bank has branches in these counties too, offering a uniform deposit price r. Now assume that the large bank decides to close its branches in counties a and b and this decision causes a change in the competition of local banking markets in these counties, inducing small banks to compete on price. On the other hand, in the focal area c there is no change in bank competition from branch closures. The research question is simplified to testing whether banks' deposit pricing in the focal area c responds to the changes in deposit pricing from socially connected markets a and b.

We argue that social connections extend the effective size of deposit markets beyond traditional geographic boundaries. In this respect, traditional market definitions based on physical distance may underestimate competitive pressure from socially connected areas and banks may respond to rate changes by competitors in socially connected areas, despite the fact that there may be no change in their local market concentration. This implies that deposit rate correlations between branches follow social connection patterns, not just geographic proximity.

4.1 Measuring social network spillovers

We construct a measure of the social proximity of households in a county c to deposit rates offered in banks in other counties. In this respect, our primary explanatory variable is *Social Deposit Rate* (*SDR*), which is county c's indirect exposure to deposit rate changes at time t via social connections with all other connected counties. This variable is computed as:

$$SDR_{c,t} = \sum_{j \in C-c} SCI_{c,j} \times \Delta r_{j,t} \quad (4)$$

where $SCI_{c,j}$ is the SCI value between counties c and j and $\Delta r_{j,t}$ is the change in deposit rates in county j at time t. We take the sum over $C - c$ which denotes all counties except the focal county c.

If two counties share many Facebook links (which implies a high SCI), then many banks in one of the counties will be exposed (indirectly) to deposit rate changes that occur in the other, and will therefore alter their deposit decisions based on the financial information transmitted. Thus, this network spillover variable assigns the largest weights to the counties that are most socially connected to county c and is plausibly exogenous to the bank deposits in the focal county.

Deposit rate changes may occur in several counties simultaneously driven by macroeconomic and monetary factors. Instead, we would like to test if deposit rate changes, following a change in local market conditions in one county, propagate across socially connected counties. For this, we focus on the indirect exposure of a bank in county c at time t to the large banks' market share changes in all socially connected areas, *Social Large Bank Market Share* (*SLBMS*) as:

$$SLBMS_{c,t} = \sum_{j \in C-c} SCI_{c,j} \times \Delta LBMS_{j,t} \quad (5)$$

where again $SCI_{c,j}$ is the SCI value between counties c and j and $\Delta LBMS_{j,t}$ is the change in market share of large banks in county j.

Finally, social connectedness is positively associated with geographic proximity and economic and cultural factors (Bailey, Cao, Kuchler, Stroebel & Wong 2018), although there is also a large degree of variation in social connectedness that cannot be explained by these factors. In our empirical specification, we use as a control the physical distance between counties. Specifically, we calculate the *Distant Deposit Rate* (*DDR*) as in eq.4 but with the weights being the inverse of the distance between each pair of counties so that the largest weights are assigned to the counties that are most geographically proximate to county c.

4.2 Empirical specification

We use our measures of social proximity defined in (4) and (5) in a two-stage least squares IV regression setup to examine whether a county's deposit rates are affected by changes in deposit rates in socially connected counties. First, we estimate:

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

and use the estimated $\widehat{SDR}_{c,t}$ in the following 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 deposit rate changes spillover effect. We control for the same set of variables as in equation 3 and add physical distance between counties *Distant Deposit Rate* (*DDR*). 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 uses the variable *Social Deposit Rate*, which takes into account deposit rate changes that occur in all other counties, and the social connections between the focal county and all other counties. This variable captures the extent to which the deposit pricing decisions of banks in a focal county are exposed to deposit rate changes that occur in other counties through social connections. Thus, the *Social Deposit Rate* will give higher weights to the exogenous deposit rate changes of highly connected vs the exogenous deposit rate changes of low connected areas.

Empirical identification relies on ensuring that the deposit rate changes used in *Social Deposit Rate* are truly exogenous. This is achieved by employing the instrument of *Social Large Bank Market Share*. By construction in equation 5, the *SLBMS* is a Bartik, *shift-share*, instrument that combines local exposure (social connections) to changes in market share of large banks in socially connected areas (Borusyak, Hull & Jaravel 2025). First, we argue that the assumption of deposit rate changes in socially connected areas, driven by changes in the local market structure of these areas (the *shift*), are exogenous to the focal county's bank deposit rates is highly plausible. Most of the socially connected counties are geographically and administratively distinct from the focal county. Banking market structure changes, such as local mergers or competitive exits, are typically confined within county or metro-area boundaries. Hence, such structural events in peer counties are unlikely to be influenced by or responsive to market conditions in the focal county. Second, we also argue that social connections (the *share*) are not confounded with the focal area's deposit rate changes nor with the deposit rate changes driven by changes in the connected counties' local market structure.[8] Finally, earlier results confirm that the change in market share of large banks in socially connected areas, $SLBMS$, is correlated with the *Social Deposit Rate*.

Taken together, with the use of the "shift-share" instrument together with the inclusion of both county and time fixed effects, our empirical strategy identifies the within-county deviation in rates $\Delta r_{c,t}$ caused by the heterogeneous exposure to exogenous deposit rate changes of socially connected areas offering robust evidence for causal interpretation of social spillovers in deposit pricing.

4.3 Panel regression estimates

To ensure that the social network has sufficient coverage across all local markets, we require its penetration rate in the US population to surpass 70%. Thus, in this second part of the empirical investigation, we use the county-year panel dataset covering the period from 2016 to 2023.[9] Moreover, to mitigate any potential confounding effects, we exclude from the

[8] According to Borusyak, Hull & Jaravel (2022) our "shift-share" instrument would be valid if it leverages many exogenous shifts even if we make no assumption on the exogeneity of the shares, in our case on social connections. Thus, this assumption could be relaxed.

[9] Facebook was launched in 2004 and despite its growth, only 50% of the U.S. adult population was using it in 2011. According to data downloaded from Statista, Facebook's penetration rate in the North America population surpassed 70% of the population in 2016 (https://www.statista.com/statistics/247614/

sample county-year observations in which (small or large) bank branch closures are taking place. In this way, we ensure that deposit rate changes in the focal area are not driven by changes in the local market's bank competition.

Table 3 shows estimates from the regression in eq. 7. First stage regression results, where changes in social connected large bank market share are used as an instrument for the change in social connected deposit rates of small banks, are not reported for brevity. In all specifications in Table 3, there is a strong positive and significant relationship suggesting that small banks in a focal area increase their deposit rates when small banks in a socially connected area increase their own deposit rates in order to adjust to the changes in local competition. This holds after controlling for geographic proximity (DDR) suggesting that our measure of social proximity of deposit rates is not simply a measure for physical proximity between counties. The variable measuring physical proximity itself is also, as expected, significant and positive consistent with greater distance from affected counties being associated with a smaller increase in deposit rate changes. Also, as GDP per capita increases and as the share of financially sophisticated customers increases in the county, the deposit rates offered by small banks increase. Higher-income areas may have more financially savvy depositors. This type of customers has stronger alternative investment options and banks in such markets may have to offer more competitive deposit rates to retain funds. Columns (5)-(8) include an interaction term between our variable SDR and a dummy for the competition level between small banks. The positive and statistically significant coefficient indicates that a more competitive environment between small banks in a county amplifies the social network spillover effect. Table 4 presents the results for the large banks and shows that, as expected from the previous empirical evidence in favour of a uniform deposit pricing independent of local market conditions, there is no significant effect on deposit rate changes.

`number-of-monthly-active-facebook-users-worldwide/`), expanding the potential impact of the social network on local banking activities. This year coincides with the acceleration of Facebook's a mobile-platform which made it easier for users to interact with content throughout the day.

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, the variable *Social Large Bank Share* 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 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	5.271***	5.420***	5.021***	6.680***	5.252***	5.427***	5.026***	6.674***
	(1.187)	(1.068)	(1.086)	(1.365)	(1.182)	(1.063)	(1.082)	(1.362)
SDR × *HighComp*					7.869**	4.913**	4.871*	4.265
					(3.189)	(2.480)	(2.488)	(2.910)
DDR	0.065***	0.038***	0.036***	0.091***	0.052***	0.030***	0.028***	0.082***
	(0.011)	(0.009)	(0.009)	(0.015)	(0.012)	(0.010)	(0.010)	(0.015)
SBHHI	0.123	0.080	0.016	-0.004	0.110	0.070	0.005	-0.007
	(0.140)	(0.168)	(0.174)	(0.056)	(0.141)	(0.168)	(0.174)	(0.056)
Seniors	-0.354	-1.717	-1.793	-0.285	-0.815	-1.996	-2.080	-0.369
	(1.185)	(1.357)	(1.404)	(0.505)	(1.198)	(1.363)	(1.411)	(0.508)
Population	0.001	-0.009	-0.007	0.003	0.000	-0.009	-0.007	0.003
	(0.006)	(0.008)	(0.008)	(0.003)	(0.006)	(0.008)	(0.008)	(0.003)
Realgdppc	0.001**	0.002**	0.002**	0.001***	0.001**	0.002**	0.002**	0.001***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
FSophistication	0.022**	0.020*	0.020*	-0.000	0.023**	0.021**	0.021*	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 4. Social connections, large bank deposit rate changes

The table reports coefficient estimates and robust standard errors (in parentheses) from second stage regressions. In the first stage, the variable *Social Large Bank Share* is used as an instrument for the *Social Deposit Rate*. The dependent variable is the change in (large 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 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	-25.39	7.57	-32.69	1,187.6
	(24.02)	(18.89)	(36.56)	(2,355.7)
DDR	-0.112***	-0.083***	-0.093***	0.246
	(0.018)	(0.014)	(0.019)	(0.577)
SBHHI	0.423***	0.231*	0.134	-0.329
	(0.160)	(0.135)	(0.220)	(0.642)
Seniors	-3.387*	2.758	3.506	-1.175
	(1.822)	(1.841)	(2.603)	(3.906)
Population	0.001	0.004	0.006	-0.010
	(0.005)	(0.004)	(0.006)	(0.019)
Realgdppc	0.004***	0.001	0.003	0.002
	(0.001)	(0.001)	(0.002)	(0.005)
FSophistication	0.020**	0.024**	0.032**	-0.016
	(0.010)	(0.010)	(0.015)	(0.032)
Obs.	8,735	8,725	8,663	7,977

4.4 *The role of financial sophistication*

Recent papers suggest that a key source of banks' market power in terms of deposit rate setting could be customers' lack of financial sophistication. Drechsler et al. (2017) show that proxies for financial sophistication (age, income, and education) are another source of market power for banks beyond concentration and that deposit spreads are more sensitive to rate changes in areas with low levels of financial sophistication. Fleckenstein & Longstaff (2024) argue that financially unsophisticated customers might invest in (or automatically roll over into) tenors with dominated rates without being aware that there are better alternatives. In contrast, if customers are financially sophisticated, then banks that offer dominated rates more frequently should have little advantage over other banks since the lower rates they offer would not be accepted. At the same time, customers with a high financial sophistication level are in general more engaged in social networks since this would require higher digital skills (Gambacorta et al. 2023).

To further illustrate the mechanism through which social connections can impact local bank concentration and thus deposit pricing of small banks, we test whether lack of financial sophistication is an additional source of market power for small banks. In doing this, we use the measure of financial sophistication which combines educational attainment and stock market participation as described in Appendix B and split the sample into high (above the median) vs low (below the median) sophisticated markets. If having a less-sophisticated customer base provides banks with market power, then this would imply that small banks in a county would be less elastic in adjusting their deposit prices in response to an exogenous change in local market competition conditions. At the same time, highly sophisticated customers are expected to be more engaged in social networks (Gambacorta et al. 2023). Thus, overall, in highly sophisticated markets social networks should play an important role in deposit pricing of small banks. Testing this mechanism provides us with a novel direct way to explore the relation between bank market power, financial sophistication of bank customers and social connections of these customers.

We investigate how financial sophistication shapes the pass-through of deposit rate shocks across socially connected areas by splitting the sample into high (the county's time-median is above the sample's median) vs low (the county's time-median is below the sample's median) sophisticated markets. The results in Table 5 make a strong case that small banks raise deposit rates in response to an exogenous change in deposit rates originated in socially connected counties when there is a large base of financially sophisticated customers. Moreover, the role of a highly competitive environment for the small banks is again validated as shown by the positive and statistically significant coefficient of the interaction term. On the other hand, results in Table 6 show that small banks operating in less sophisticated markets do not change their deposit rates. These results provide support to the view, 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. In turn, this implies that financial sophistication may play a central role in amplifying the online social network effect in deposit pricing since higher financial sophistication is associated with higher online social interaction.

Table 5. Social connections, small bank deposit rate changes and high sophisticated markets
The table reports coefficient estimates and robust standard errors (in parentheses) from second stage regressions. In the first stage, the variable *Social Large Bank Share* 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 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	6.329***	6.003***	5.995***	7.416***	6.673***	6.249***	6.256***	7.616***
	(0.863)	(0.848)	(0.813)	(1.068)	(0.869)	(0.846)	(0.813)	(1.055)
SDR $\times$ *HighComp*					7.038***	4.999**	5.199**	3.840
					(2.538)	(2.080)	(2.051)	(2.515)
DDR	0.063***	0.038***	0.031***	0.084***	0.041***	0.022	0.014	0.071***
	(0.013)	(0.012)	(0.012)	(0.017)	(0.015)	(0.014)	(0.013)	(0.018)
SBHHI	0.106	0.238	0.183	0.136*	0.106	0.239	0.184	0.136*
	(0.206)	(0.247)	(0.258)	(0.073)	(0.205)	(0.247)	(0.257)	(0.073)
Seniors	-0.407	-0.796	-1.046	-0.127	-0.514	-0.841	-1.102	-0.136
	(1.564)	(1.834)	(1.913)	(0.675)	(1.562)	(1.831)	(1.910)	(0.675)
Population	0.008	-0.007	-0.009	0.003	0.008	-0.007	-0.009	0.003
	(0.006)	(0.010)	(0.011)	(0.003)	(0.006)	(0.010)	(0.010)	(0.003)
Realgdppc	-0.000	0.000	-0.000	0.000	-0.000	0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Obs.	7,661	7,672	7,649	7,613	7,661	7,672	7,649	7,613

Table 6. Social connections, small bank deposit rate changes and low sophisticated markets

The table reports coefficient estimates and robust standard errors (in parentheses) from second stage regressions. In the first stage, the variable *Social Large Bank Share* 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 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	97.580	-5.217	-51.277	22.783	54.418	-6.163	-67.572	20.140
	(450.149)	(25.180)	(173.178)	(21.648)	(130.642)	(27.783)	(294.054)	(17.994)
SDR × *HighComp*					-47.807	8.281	46.472	-17.495
					(165.006)	(26.358)	(215.938)	(36.032)
DDR	-0.469	0.089	0.339	-0.042	-0.167	0.085	0.378	0.003
	(2.566)	(0.136)	(0.949)	(0.167)	(0.577)	(0.133)	(1.394)	(0.119)
SBHHI	-0.866	0.055	0.335	-0.117	-0.322	0.045	0.355	-0.103
	(4.817)	(0.364)	(1.569)	(0.087)	(1.182)	(0.361)	(2.099)	(0.088)
Seniors	13.890	-4.489	-13.885	0.853	10.281	-5.207	-20.391	1.041
	(69.643)	(5.738)	(37.391)	(1.709)	(30.147)	(7.392)	(76.465)	(1.954)
Population	0.196	-0.039	-0.150	0.016	0.126	-0.046	-0.221	0.017
	(1.004)	(0.066)	(0.460)	(0.020)	(0.377)	(0.083)	(0.899)	(0.022)
Realgdppc	-0.017	0.006	0.016	0.000	-0.007	0.006	0.019	0.000
	(0.097)	(0.006)	(0.039)	(0.002)	(0.027)	(0.006)	(0.063)	(0.001)
Obs.	9,501	9,519	9,503	9,442	9,501	9,519	9,503	9,442

4.5 Robustness tests

In this section we offer additional robustness test to preclude alternative channels such as geographical and economic proximity. Furthermore, we use time-varying data from the residential fixed broadband connections to ensure that the "active" social connections are the true channel.

4.5.1 Geographical proximity

The validity of our empirical identification strategies relies on the assumption that the socially connected counties are geographically and administratively distinct from the focal county. Our main results control for the distance between socially connected counties using a distance-weighted measure of deposit rates (DDR). In this section, we offer additional tests that confirm that our measure of social proximity of deposit rates is not confounded with physical proximity. Specifically, we repeat the estimation of the previous tests for the social connections effect on deposit rates after excluding all counties within 25-mile and 50-mile radius from the focal county c from the calculation of the social-connections weighted variables in equations (4)-(5). This ensures that counties are geographically distant "enough" and the only connection is though social networks.

Table 7 replicates tests presented in Table 3 after excluding connected counties within the 25-mile radius of the focal county c, while Tables 8- 9 are the replicated tests corresponding to the above Tables 5 and 6 respectively. Equivalently, Tables 10-12 present the same tests after excluding connected counties within the 50-mile radius of the focal county. Despite some expected changes in the estimated coefficients, results remain largely similar both in terms of statistical significance. Moreover, the economic significance of the estimates incrementally increased as we remove the 25-miles and then the 50-miles proximate counties. This finding largely suggests that the effect of social connections becomes more profound as the distance between two peer markets increases.

Overall, the tests in this section offer robust evidence that social proximity acts as a separate channel from geographical proximity for the transmission of changes in small banks deposit pricing caused by local market competition changes.

Table 7. 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, the variable *Social Large Bank Share* 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 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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	6m10K	12m10K	12m100K	mm10k	6m10K	12m10K	12m100K	mm10k
SDR	6.619***	6.973***	6.667***	9.160***	6.482***	6.884***	6.577***	9.048***
	(1.217)	(1.180)	(1.157)	(1.394)	(1.219)	(1.185)	(1.164)	(1.400)
SDR × *HighComp*					7.642*	6.741**	6.678**	7.336*
					(3.974)	(3.276)	(3.261)	(3.824)
SBHHI	0.156	0.096	0.025	0.007	0.145	0.084	0.012	0.004
	(0.140)	(0.168)	(0.173)	(0.057)	(0.141)	(0.168)	(0.174)	(0.057)
Seniors	0.134	-1.514	-1.594	-0.047	-0.319	-1.901	-1.988	-0.195
	(1.190)	(1.365)	(1.410)	(0.507)	(1.204)	(1.369)	(1.416)	(0.510)
Population	0.006	-0.005	-0.003	0.006**	0.004	-0.007	-0.005	0.006**
	(0.006)	(0.008)	(0.008)	(0.003)	(0.006)	(0.007)	(0.008)	(0.003)
Realgdppc	0.001	0.001*	0.001*	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	0.020**	0.018*	0.018*	-0.002	0.021**	0.020*	0.019*	-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 8. Social connections, small bank deposit rate changes and high sophisticated markets - 25miles radius The table reports coefficient estimates and robust standard errors (in parentheses) from second stage regressions. In the first stage, the variable *Social Large Bank Share* 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 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	7.215***	7.377***	7.339***	8.973***	7.472***	7.622***	7.571***	9.235***
	(1.025)	(0.985)	(0.941)	(1.191)	(1.025)	(0.990)	(0.946)	(1.173)
SDR $\times$ *HighComp*					5.976*	5.431**	5.311**	6.380**
					(3.130)	(2.686)	(2.624)	(3.063)
SBHHI	0.166	0.284	0.227	0.172**	0.164	0.281	0.223	0.172**
	(0.207)	(0.248)	(0.259)	(0.074)	(0.206)	(0.247)	(0.258)	(0.074)
Seniors	0.200	-0.487	-0.822	0.192	-0.008	-0.653	-0.991	0.113
	(1.587)	(1.874)	(1.950)	(0.682)	(1.580)	(1.867)	(1.943)	(0.680)
Population	0.012*	-0.006	-0.008	0.005*	0.011*	-0.006	-0.008	0.005*
	(0.007)	(0.010)	(0.010)	(0.003)	(0.006)	(0.010)	(0.010)	(0.003)
Realgdppc	-0.001	-0.000	-0.000	0.000	-0.000	-0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Obs.	7,661	7,672	7,649	7,613	7,661	7,672	7,649	7,613

Table 9. Social connections, small bank deposit rate changes and low sophisticated markets - 25miles radius
The table reports coefficient estimates and robust standard errors (in parentheses) from second stage regressions. In the first stage, the variable *Social Large Bank Share* 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 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	-13.347	-20.928	4.445	-34.124	10.910	8.315	11.486	5.944
	(61.830)	(86.789)	(35.817)	(89.834)	(13.315)	(17.096)	(12.061)	(29.163)
SDR × *HighComp*					22.377	25.162	9.790	53.145
					(42.511)	(47.355)	(42.161)	(83.557)
SBHHI	0.279	0.179	-0.097	-0.096	0.095	-0.091	-0.169	-0.136
	(0.435)	(0.706)	(0.334)	(0.131)	(0.220)	(0.273)	(0.251)	(0.099)
Seniors	-2.854	-7.280	-1.822	-3.073	-0.246	-2.952	-1.013	-1.200
	(10.559)	(17.795)	(7.539)	(6.792)	(3.710)	(5.119)	(4.679)	(1.803)
Population	-0.036	-0.056	-0.003	-0.016	-0.013	-0.021	0.004	-0.008
	(0.093)	(0.148)	(0.062)	(0.045)	(0.031)	(0.043)	(0.041)	(0.014)
Realgdppc	0.007	0.009	0.004	0.004	0.001	0.003	0.002	0.001
	(0.013)	(0.018)	(0.008)	(0.006)	(0.003)	(0.004)	(0.003)	(0.002)
Obs.	9,501	9,519	9,503	9,442	9,501	9,519	9,503	9,442

Table 10. 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, the variable *Social Large Bank Share* 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 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	7.525***	8.726***	8.660***	11.318***	7.666***	8.770***	8.699***	11.375***
	(1.465)	(1.375)	(1.330)	(1.630)	(1.461)	(1.367)	(1.324)	(1.618)
SDR × *HighComp*					10.664	2.513	2.410	8.049
					(9.637)	(6.088)	(6.141)	(6.967)
SBHHI	0.179	0.126	0.050	0.011	0.166	0.122	0.047	0.008
	(0.142)	(0.171)	(0.175)	(0.057)	(0.143)	(0.171)	(0.176)	(0.057)
Seniors	0.141	-1.433	-1.466	-0.060	-0.245	-1.521	-1.554	-0.166
	(1.204)	(1.366)	(1.416)	(0.509)	(1.245)	(1.377)	(1.429)	(0.514)
Population	0.005	-0.006	-0.004	0.006**	0.004	-0.006	-0.004	0.005**
	(0.006)	(0.007)	(0.008)	(0.003)	(0.006)	(0.007)	(0.008)	(0.003)
Realgdppc	0.001	0.001	0.001*	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	0.024***	0.023**	0.021**	-0.000	0.025***	0.023**	0.022**	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 11. Social connections, small bank deposit rate changes and high sophisticated markets - 50miles radius
The table reports coefficient estimates and robust standard errors (in parentheses) from second stage regressions. In the first stage, the variable *Social Large Bank Share* 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 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	10.292***	10.482***	10.751***	12.008***	10.654***	10.593***	10.878***	12.530***
	(1.532)	(1.462)	(1.404)	(1.626)	(1.543)	(1.466)	(1.414)	(1.594)
SDR × *HighComp*					4.877	1.405	1.654	7.955
					(5.718)	(4.404)	(4.333)	(5.266)
SBHHI	0.157	0.298	0.242	0.177**	0.153	0.297	0.241	0.175**
	(0.210)	(0.251)	(0.261)	(0.074)	(0.209)	(0.251)	(0.260)	(0.074)
Seniors	0.611	0.111	-0.111	0.293	0.555	0.103	-0.121	0.244
	(1.598)	(1.865)	(1.944)	(0.686)	(1.594)	(1.863)	(1.943)	(0.686)
Population	0.012*	-0.005	-0.007	0.006**	0.012*	-0.005	-0.007	0.005**
	(0.006)	(0.010)	(0.010)	(0.003)	(0.006)	(0.010)	(0.010)	(0.003)
Realgdppc	-0.001	-0.001	-0.001	0.000	-0.001	-0.001	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Obs.	7,661	7,672	7,649	7,613	7,661	7,672	7,649	7,613

Table 12. Social connections, small bank deposit rate changes and low sophisticated markets - 50miles radius
The table reports coefficient estimates and robust standard errors (in parentheses) from second stage regressions. In the first stage, the variable *Social Large Bank Share* 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 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	-27.406	1.978	-10.721	19.377	-21.780	2.752	-9.453	15.898
	(38.013)	(19.936)	(26.384)	(17.311)	(32.331)	(18.775)	(24.432)	(16.501)
SDR × *HighComp*					-33.050	-9.300	-12.991	27.525
					(29.820)	(21.801)	(25.211)	(39.333)
SBHHI	0.232	0.021	-0.042	-0.104	0.254	0.029	-0.030	-0.114
	(0.259)	(0.242)	(0.272)	(0.082)	(0.248)	(0.244)	(0.273)	(0.084)
Seniors	-3.946	-2.851	-4.209	0.416	-1.932	-2.349	-3.464	-0.138
	(5.108)	(3.527)	(4.445)	(1.165)	(4.185)	(3.136)	(3.876)	(1.206)
Population	-0.038	-0.019	-0.020	0.005	-0.020	-0.015	-0.013	0.001
	(0.031)	(0.022)	(0.028)	(0.008)	(0.025)	(0.019)	(0.023)	(0.008)
Realgdppc	0.007	0.004	0.006*	0.001	0.007	0.004	0.006*	0.001
	(0.005)	(0.003)	(0.004)	(0.001)	(0.004)	(0.003)	(0.004)	(0.001)
Obs.	9,501	9,519	9,503	9,442	9,501	9,519	9,503	9,442

4.5.2 Economic proximity

In this section, we follow Flynn & Wang (2022) to account for potential existing economic linkages between counties due to similarities in industry composition. This is because if two counties share similar industrial structures, then these may share stronger economic ties, such as through trade, labor mobility or migration patterns. As in Flynn & Wang (2022) a county's industry composition is measured employment data by industry from the Bureau of Labor Statistics' (BLS) Quarterly Census of Employment and Wages. For each county-year, we compute the share of total county employment in each 2-digit NAICS sector and calculate the cosine similarity of industry employment shares for each county pair in each year denoted as $EP_{c,j,t}$. We then construct the *Economic Proximity Deposit Rate* (*EPDR*) variable to control for the indirect exposure of county c to deposit rate changes in economically connected counties:

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

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

Columns (1)-(4) in Table (13) shows that after including *Economic Proximity Deposit Rate* in our baseline specifications, the effect of our main variable of interest, Social (Proximity to) Deposit Rate, remains positive and significant, while the Economic Proximity Deposit Rate is consistently insignificant. This suggests that our main findings are unlikely to be driven by underlying economic linkages between counties, validating the role of social networks as the main channel.

Table 13. 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, the variable *Social Large Bank Share* is used as an instrument for the *Social Deposit Rate* and we additionaly control for economic connections between counties. In columns (5)-(8), in the first stage, 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. 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	5.341***	5.522***	5.114***	6.821***	7.671***	6.989***	7.193***	8.713***
	(1.250)	(1.128)	(1.143)	(1.456)	(1.091)	(1.034)	(1.009)	(1.269)
DDR	0.064***	0.037***	0.035***	0.088***	0.065***	0.045***	0.039***	0.095***
	(0.012)	(0.010)	(0.010)	(0.016)	(0.010)	(0.008)	(0.008)	(0.012)
EPDR	0.049	0.067	0.063	0.095				
	(0.068)	(0.060)	(0.060)	(0.088)				
SBHHI	0.118	0.073	0.008	-0.007	0.143	0.111	0.035	0.008
	(0.141)	(0.169)	(0.174)	(0.056)	(0.144)	(0.171)	(0.177)	(0.056)
Seniors	-0.353	-1.695	-1.770	-0.280	-0.369	-1.711	-1.717	-0.328
	(1.185)	(1.358)	(1.405)	(0.505)	(1.241)	(1.405)	(1.461)	(0.509)
Population	0.001	-0.009	-0.007	0.003	0.002	-0.008	-0.006	0.003
	(0.006)	(0.008)	(0.008)	(0.003)	(0.006)	(0.008)	(0.008)	(0.003)
Realgdppc	0.001**	0.002**	0.002**	0.001***	0.000	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
FSophistication	0.022**	0.020*	0.020*	-0.000	0.026***	0.026**	0.026**	0.002
	(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

4.5.3 Residential broadband connections

In this section, we use residential fixed broadband connections as a variable for digital access and internet penetration at the local level. Higher values indicate greater household internet connectivity, which likely facilitates peer interaction through online social networks. For this, we use Internet Access Services Speed Tier Data at county level from the Federal Communications Commission (FCC).

Specifically, we recalculate both the *Social Deposit Rate* (*SDR*) and the indirect exposure of county c to large banks' market share changes, *Social Large Bank Market Share* (*SLBMS*), at time t to control for internet access:

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

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

where $I_{c,t}$ and $I_{j,t}$ are indicators taking the value of 1 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.[10]

This identification strategy relies on the variability of residential broadband connections over time as a proxy of the activity of local households in social media. Social connections between counties c and j are only included in the calculation of $SDR^{rob}_{c,t}$ when both counties exceed the broadband threshold of 40%, ensuring that the $SDR^{rob}_{c,t}$ varies over time in association with meaningful digital connectivity, i.e. these are real "active" social connections. Results presented in columns (5)-(8) in Table 13 show that our main findings remain robust when accounting for internet access in measuring social connections, supporting our claim that online social networks is the channel for the transmission of deposit rate shocks.

[10] The choice of 40% as the threshold is based on the data available which splits the population into five tiers: from 0-20% to 80-100%.

5 Social connections and uniform pricing

The previous section offers empirical evidence that social connections transmit financial information and in this way affect small banks' deposit price-setting decisions in socially connected areas. A corollary of these findings is that as the social network engagement of the customers of small banks intensifies, small banks will tend to setting the same price across all socially connected counties given that the information is distributed more quickly across banks and across counties. In this section, we test for this corollary, i.e. whether increased social linkages are associated with uniformity in small bank deposit rates across socially connected areas, effectively diminishing local pricing heterogeneity and promoting convergence towards an equilibrium deposit rate.

For this, we employ a β-convergence model which is typically used to test whether regions (countries, counties, or other units) with initially lower levels of some variable (for example, GDP per capita) grow faster than those with higher levels and thus, eventually catch up over time and converge (Barro & Sala-i Martin 1992, Kremer, Willis & You 2022).

In its simplest form, the β-convergence model is the following:

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

where Y is the outcome variable of interest and a negative, statistically significant β indicates convergence as lower lagged values of Y result in higher growth rate and vice versa.

In our case, the variable of interest is $(r_{c,t} - r^{sc}_{c,t})$, i.e. the gap between the deposit rates $r_{c,t}$ of small banks in a county c, and the weighted average of deposit rates of its 'social peers' defined as $r^{sc}_{c,t} = \sum_{j \in C-c} \frac{SCI_{c,j}}{\sum_{j \in C-c} SCI_{c,j}} r_{j,t}$ shrink over time. Thus, the outcome variable would be $\Delta(r_{c,t} - r^{sc}_{c,t}) = (r_{c,t} - r^{sc}_{c,t}) - (r_{c,t-1} - r^{sc}_{c,t-1})$.

Our SCI data is not available for multiple time periods but it is a snapshot of 2020 Facebook links. This time-invariance was not an issue when we implemented the Bartik-style, share-shift instrument given the requirement for the stability of shares. Nonetheless, our aim now is to test whether increased use of social networks speeds the convergence of deposit rate changes of small banks. Thus, to capture time-variation of the intensity of social network use we define $SC_{c,t-1} = \sum_{j \in C-c} SCI_{c,j} \times U_t$, where U_t is the number of total users U_t of the social network at time t and county c. We then test for the speed of convergence due to social spillovers by adding to β-convergence model equation 11 the interaction term $SC_{c,t-1} \times (r_{c,t-1} - r^{sc}_{c,t-1})$.[11] Specifically, we estimate the panel model:

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

where $x_{c,t}$ is the same set of control variables, f_c and f_t are the county- and time-fixed effects and $\epsilon_{c,t}$ is the error term clustered at the county level.

The proposed identification strategy, employing a difference-in-differences (DiD) specification in a panel data context, allows for a causal interpretation by removing both county-specific and common temporal trends. By using the change, the dependent variable removes any macroeconomic shocks or policy-driven trends which might affect counties over time. Moreover, including county fixed effects absorbs any unobserved heterogeneity such as persistent differences in local economic conditions or banking market structure differences. The parameter of interest is the interaction effect α_2 with a negative sign implying that as social connections intensify, counties with initially higher deposit rates than the weighted average of their socially connected counties tend to decrease systematically their rates and the contrary holds for the counties initially below the connected counties' average. Thus, the interaction effect offers a test whether social networks accelerate the convergence of rates toward a common equilibrium value.

We estimate the model equation 12 using quarterly data from 2011q2 to 2023q3. During this period, the number of Facebook monthly active users (MAU) in the United States (and

[11] SCI data is not available for multiple time periods. However, 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.

Canada) grew from 163 millions to 271 millions, a 66% increase.[12]

The negative and statistically significant estimate of α_2 in columns (1)-(3) in Table 14 indicates clear evidence of convergence in deposit rates driven by social connections. The only exception is for the money market accounts in column (4) where the result is negative but not significant. At the same time, the negative and statistically significant estimate of β in Table 14 suggests that convergence is taking place beyond social network spillovers. This could be partially explained by the consolidation wave of small and medium banks inducing business models of smaller banks to look more like multi-market banks. Similarly, online banks act as a new omnipresent competitor pricing deposits independent of the local market geographic borders, pushing local banks to revise their deposit prices. Finally, the growth of the internet offers alternative channels for financial information transmission promoting further uniform pricing. All in all, our empirical results show that although there is evidence for convergence of deposit rates of small banks through time, due to many possible reasons, social networks play a key and distinct role in the speed of convergence.

As in our baseline analysis, we anticipate that if market concentration of small banks in the county is low, then competitive forces will amplify the effect of social networks on uniform pricing. To test this, we triple interact the variable $SC_{c,t-1}$ in eq.13 with the dummy ($HighComp$) in the following specification:

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

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

The negative and statistically significant estimate of α_4 in columns (5)-(8) in Table 14 shows that convergence is observed in markets with high competition between small banks. This holds even for money market accounts which was previously insignificant. In most case, the interaction effect α_2 of social connections with the rating gap for highly concentrated, less competitive markets is not significant.

Meanwhile, the net effect assuming away the social network effects, $\beta = (\beta_1 + \beta_2 \times HighComp)$ of the rate gap $(r_{c,t-1} - r^{sc}_{c,t-1})$ is negative. For example, for 6-month deposits the estimated effect is $\beta_1 = -0.105$ for low competition ($HighComp = 0$) and remains negative although smaller in magnitude for highly competitive markets ($HighComp = 1$), i.e. $\beta_1 + \beta_2 = -0.105 + 0.078 = -0.027$. These findings suggest that small banks' deposit rate convergence takes place independent of the social connectivity although this effect is smaller for highly competitive markets. The latter observation could be explained by the fact that local competition forces small banks to price deposits locally, reducing, but not reversing, the overarching uniform pricing trend.

To address concerns that our results may be driven by convergence of deposit rates between small banks located in counties with physical proximity (low distance), we repeat the above analysis after removing from the calculation of $r^{sc}_{c,t}$ all counties with a distance less than 25miles and all counties with a distance less than 50 miles. The results are presented in Table 15 and Table 16 respectively. The findings from these two robustness tests are economically and statistically equivalent with the results of Table 14.

Next, we estimate the panel model (12) for large banks deposit rates. We find scarce evidence of social connectivity driven convergence in deposit rates as the coefficient α_2 in columns (1)-(4) in Table 17 is statistically insignificant. However, as expected, the main effect of the rate gap $(r_{c,t-1} - r^{sc}_{c,t-1})$ is negative and statistically significant. This finding is consistent with the literature predicting that structural forces such as the growth in Internet and online banking, may reinforce large (multi-market) bank's uniform rates practice across locations (Park & Pennacchi 2008). The lack of evidence for social network spillover effect on convergence for the large banks can potentially be explained by the fact that branches of large multi-market banks, transmit the necessary information to the central, rate-setting branch which then determines a uniform rate across all regions.

Overall, our results show that increased social linkages effectively diminish regional pricing disparities of small banks by enhancing the speed of adjustment toward common levels. This effect is found in parallel with the convergence in bank deposit rates observed across banks that is taking place possibly due to technological advancements that reduce the importance of geographic distance in banking.

Table 14. 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)
$SC \times (r_{c,t-1} - r^{sc}_{c,t-1}) \times HighComp$					-0.008***	-0.006***	-0.003**	-0.005***
					(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***	-0.105***	-0.122***	-0.103***	-0.120***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.006)	(0.005)	(0.005)	(0.005)
$(r_{c,t-1} - r^{sc}_{c,t-1}) \times HighComp$					0.078***	0.060***	0.057***	0.044***
					(0.012)	(0.010)	(0.010)	(0.010)
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***	-0.174***	-0.161***	-0.152***	-0.059***
	(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***	0.006	0.016*	0.018*	0.015***
	(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	0.001	-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***	-0.001	-0.033	-0.042	-0.047***
	(0.032)	(0.037)	(0.038)	(0.015)	(0.032)	(0.037)	(0.038)	(0.015)
Obs.	143,461	143,555	144,811	142,890	143,461	143,555	144,811	142,890

Table 15. 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)
$SC \times (r_{c,t-1} - r^{sc}_{c,t-1}) \times HighComp$					-0.010***	-0.008***	-0.004***	-0.005***
					(0.002)	(0.002)	(0.002)	(0.002)
$(r_{c,t-1} - r^{sc}_{c,t-1})$	-0.086***	-0.104***	-0.081***	-0.112***	-0.099***	-0.114***	-0.095***	-0.119***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)
$(r_{c,t-1} - r^{sc}_{c,t-1}) \times HighComp$					0.074***	0.059***	0.055***	0.041***
					(0.012)	(0.010)	(0.010)	(0.010)
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**	0.001*	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***	-0.180***	-0.178***	-0.175***	-0.060***
	(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***	0.009	0.017*	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***	-0.009	-0.037	-0.039	-0.052***
	(0.032)	(0.037)	(0.038)	(0.015)	(0.032)	(0.037)	(0.038)	(0.015)
Obs.	143,461	143,555	144,811	142,890	143,461	143,555	144,811	142,890

Table 16. 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	-0.002***	-0.001**	-0.001***	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$SC \times (r_{c,t-1} - r^{sc}_{c,t-1}) \times HighComp$					-0.012***	-0.012***	-0.006***	-0.007***
					(0.003)	(0.002)	(0.002)	(0.002)
$(r_{c,t-1} - r^{sc}_{c,t-1})$	-0.076***	-0.098***	-0.076***	-0.110***	-0.087***	-0.107***	-0.088***	-0.117***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
$(r_{c,t-1} - r^{sc}_{c,t-1}) \times HighComp$					0.063***	0.055***	0.051***	0.038***
					(0.011)	(0.010)	(0.010)	(0.009)
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**	0.001***
					(0.001)	(0.001)	(0.001)	(0.001)
SBHHI	-0.014**	-0.015*	-0.018**	-0.004	-0.013**	-0.014*	-0.018**	-0.004
	(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***	-0.232***	-0.237***	-0.239***	-0.069***
	(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***	0.008	0.018*	0.020**	0.019***
	(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***	0.002	-0.031	-0.037	-0.058***
	(0.031)	(0.037)	(0.038)	(0.015)	(0.032)	(0.037)	(0.038)	(0.015)
Obs.	143,461	143,555	144,811	142,890	143,461	143,555	144,811	142,890

Table 17. 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

6 Conclusions

We introduce a new determinant of local deposit rates and banks' pricing power: social networks. While previous research has established social connections as a key driver of consumer decision-making, these interactions serve as a distinct channel for transmitting valuable financial insights. We contribute novel evidence by investigating how households' social connections affect deposit pricing in small banks.

First, we confirm previous findings that large banks price uniformly while providing new evidence that small banks price deposits based on local market conditions. After a merger-induced branch closure of a large bank, small banks offer higher rates to attract depositors while large banks do not respond since they compete on other non-price services. For example, superior liquidity services provided by large banks make customers less rate-sensitive. On the other hand, small banks set their rates depending on the competition conditions in the local market, since both their customer base and business models are different to large banks.

Second, leveraging exogenous shifts in local market structure in socially connected areas, we assess the subsequent impact on small banks' deposit rate changes. We construct a measure of social proximity of deposit rates using county level data on social networks and find 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. We confirm that our measure does not capture geographic proximity or economic connections as well as that it takes into account "active" social connections in a battery of robustness checks.

Third, to isolate the social networks spillover effect, we use a proxy for the financial sophistication level of customers combining educational attainment and stock market participation. Having a less-sophisticated customer base provides banks with market power and these customers are less engaged in social networks. When splitting the sample into high vs low sophistication, we confirm our hypothesis that the effect of social ties is strong and persistent in highly sophisticated markets.

Finally, a corollary of our findings is that small banks will eventually converge to a common price they offer across all socially connected counties as social network intensity increases. Interestingly, we find that the gap between the deposit rates offered by both small and large banks in a county and those offered by their peers shrinks over time as new technologies reduce the importance of geographic distance. However, social spillover effects play a key role in the speed of convergence towards a common deposit rate only for the small banks validating further our baseline results.

Our findings underscore the significance of social networks in shaping deposit rate policies and offer new insights into the behavioral forces driving local banking markets.

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A Additional information on data

Table A1. Summary statistics of deposit rates (time-differences)

	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 control variables (time-differences)

Stats	**ΔSBHHI**	**ΔFsophistication**	**ΔRealgdppc**	**ΔPopulation**	**ΔSeniors**	**ΔLBMS**
N	35,088	35,088	35,088	35,088	35,088	35,088
Mean	0.002	0.100	0.606	0.601	0.004	0.002
SD	0.020	0.341	4.049	2.172	0.003	0.021
p1	-0.065	-1.060	-14.320	-1.814	-0.004	-0.083
p50	0.000	0.098	0.415	0.010	0.004	0.000
p99	0.097	1.253	19.772	14.741	0.012	0.104

B 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 A1 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 A3). 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 A4 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 A1. Line plot of the eigenvalues of principal components analysis.

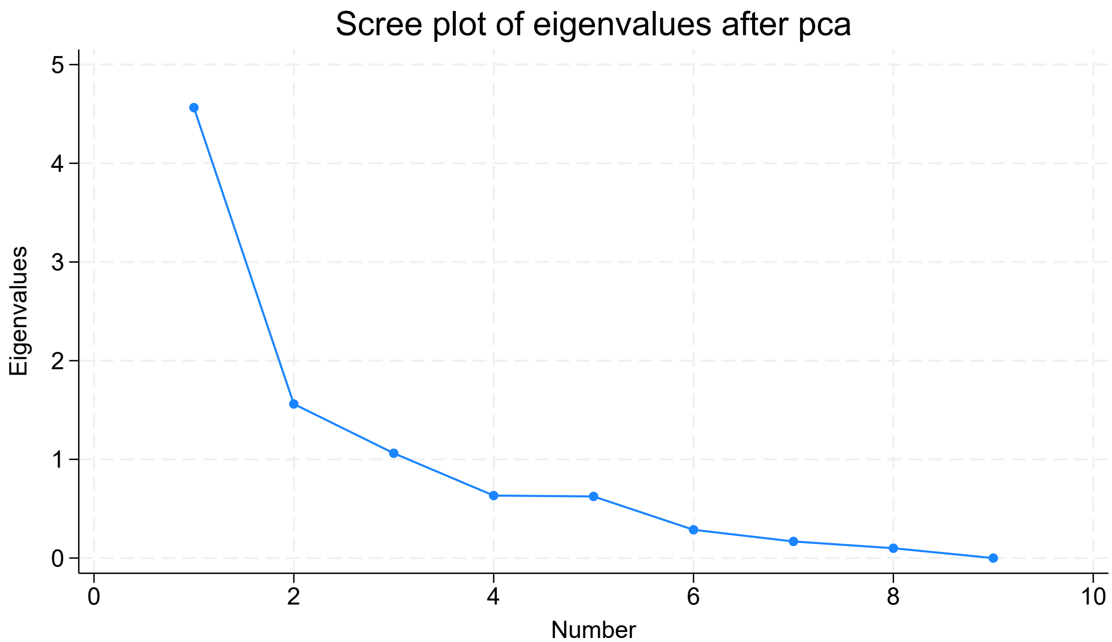

Table A3. Principal components analysis: Top four components

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 A4. 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