Social Connections and Bank Deposit Funding*

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Abstract

We show that social connections transmit shocks that influence banks' deposit funding. We find that counties experience an increase in bank deposits when they are more socially connected to counties affected by natural disasters, consistent with heightened precautionary saving incentives. This effect is not driven by physical proximity, large disasters that attract significant media coverage, or other cross-county channels, including multimarket bank branch networks, population migration, economic similarity, and depositors living on the border of disaster-affected counties. Banks that collect deposits in highly socially-connected counties experience high deposit volatility, but geographic diversification reduces the volatility associated with depositor social connectedness.

Keywords: Social connections, Bank deposits, Bank funding stability, Natural disasters

JEL classification: G21, O16, D14

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1 Introduction

Bank deposits constitute the most important aspect of banks' value creation and play a central role in the availability of credit for economic activities (see, e.g., Egan, Lewellen, and Sunderam (2022)). Thus, understanding the determinants of deposit funding is important. The literature has explored a variety of factors—such as depositors' demographic characteristics, bank deposit market power, and stock market performance—that influence bank deposits (e.g., Becker (2007), Drechsler, Savov, and Schnabl (2017), and Lin (2020)). In this paper, we explore a new determinant of bank deposit funding: households' social connections.

Our research question is motivated by two simple yet consequential observations. First, banks rely heavily on household deposits for funding. Second, households tend to draw on the experiences of their friends and family in making financial decisions (e.g., Bailey, Cao, Kuchler, and Stroebel (2018a), Bailey, Davila, Kuchler, and Stroebel (2019), Hu (2022), and Hung (2021)). Based on these observations, we hypothesize that social connections may influence bank deposits by transmitting shocks to households' saving incentives.

Ex-ante, it is unclear whether shocks transmitted via social connections would necessarily aggregate up to have a first-order impact on bank deposits. Compared with prior studies that show that social connections influence financial outcomes for individuals, the answer to our research question can shed light on whether social connections influence the funding to one of the most important sectors of the capital markets—banks.

To test the hypothesis that social connections influence bank deposits, we examine whether a county's deposits are affected by shocks experienced by households in other counties, depending on the intensity of social connections between the focal county and other counties. The shocks that we exploit in this paper are natural disasters. We propose that natural disasters experienced by social connections (even when they are geographically distant) are likely to increase the salience of negative events for a given household, despite the fact that there may be no change in actual risk. The increase in salience occurs due to the emotional connection between individuals and their social connections (such as friends and relatives). This leads households to change their beliefs about the likelihood of negative events occurring, or makes them more aware of the consequences of negative events. Subsequently, the heightened salience of negative events incentivizes households to increase bank deposit demand for precautionary reasons.[1] If more households in the focal county are connected to households in disaster-affected areas, then these disasters are likely to have a larger impact on bank deposits in the focal county through social connections. As a result, counties that are more socially connected to disaster-affected areas should experience a greater increase in bank deposits relative to other counties.

Although our empirical strategy uses natural disasters to identify the effect of shocks transmitted through social connections, we do not presuppose that households change only their perceptions about natural disaster risk following the occurrence of a disaster in a friend's geographic region. Rather, based on evidence in existing literature, we assume that natural disasters experienced by social connections can change households' perceptions about risk and outcomes associated with negative events in general.[2] It is also important to note that, in addition to shocks related to negative experiences, such as the disasters exploited in this study, social connections may transmit shocks related to positive experiences as well. If the

[1] Recent studies suggest that individuals' beliefs about various events are shaped by events that their social connections experience. Bailey, Cao, Kuchler, and Stroebel (2018a) and Bailey, Davila, Kuchler, and Stroebel (2019) show that friends' experiences in the housing market influence individuals' beliefs about the value of renting vs owning, house price changes, and choice of leverage. Similarly, Hu (2022) shows that hurricanes experienced by geographically-distant social connections can influence households' use of flood insurance.

[2] Existing literature documents a broad range of experiences that impact decision subsequent making by increasing the salience of negative events. Bernile, Bhagwat, and Rau (2017) show that highly-damaging natural disasters experienced by CEOs during their formative years result in more conservative risk-taking behavior. Betzer, Limbach, Rau, and Schurmann (2021) show that fund managers who experience family disruption early in life tend to take lower risk in their investment portfolio. In addition to early life events, a CEO's very recent experiences can affect subsequent decision making through a salience channel. Dessaint and Matray (2017) show that firms located in close proximity to hurricane-affected areas temporarily increase cash holdings and mention hurricane-related risks in regulatory filings more, despite the fact that the firm has experienced no change in the actual likelihood of a hurricane. Finally, literature suggests that past *professional* experiences can also impact future decisions through a salience channel. See, e.g., Dittmar and Duchin (2016).

salience of positive experiences increases, households may instead reduce deposit demand due to a reduction in precautionary saving incentives.[3]

We measure the intensity of social connections between pairs of counties using the Social Connectedness Index (hereafter SCI) developed by Bailey, Cao, Kuchler, Stroebel, and Wong (2018b) and available from Facebook. This index is based on Facebook connections between residents of different counties and is used in recent studies as a proxy for unobservable real-world social connections (see, e.g., Kuchler, Li, Peng, Stroebel, and Zhou (2022) and Hu (2022)). The SCI is particularly relevant for our research question because Facebook is mainly used to connect with real-world friends and family whose experiences are most likely to have a significant impact on households' financial decisions. Moreover, compared with other platforms, Facebook has persistent popularity and coverage in the U.S., making it possible to study our research question over a long period.

Our identification comes from the key variable that captures each county's *indirect* exposure (via social connections) to natural disasters that occur in other counties. The level of exposure is jointly determined by the intensity of social connections and the occurrence of natural disasters in other counties, such that this variable is calculated in two steps for each county-year. In the first step, we calculate a focal county's indirect exposure to natural disasters that occur in another county by multiplying the pairwise SCI value between the two counties with a measure of natural disasters in the other county. If two counties share many Facebook links (which implies a high pairwise SCI), then many households in one of the counties will be exposed (indirectly) to disasters that occur in the other, and will therefore alter their deposit decisions based on awareness of these disasters. In the second step, we add up the focal county's indirect exposure to natural disasters that have occurred in all other counties. Because the occurrence of natural disasters in other counties is random, this measure of indirect exposure to disasters via social connections is plausibly exogenous

[3]Existing literature suggests that positive experience can lead to more risk taking. For example, Gopalan, Gormley, and Kalda (2021) show that directors who have positive experiences with bankruptcy (such as shorter and less costly bankruptcies) take more risk at other firms where they concurrently serve.

to bank deposits in the focal county.

Using this empirical design, we find evidence consistent with our hypothesis. Specifically, we find that deposits in a focal county are significantly higher when households in that county are more exposed to natural disasters in other counties via their social connections. This result holds when controlling for both the contemporaneous disaster experience of the focal county and the physical distance between the focal county and disaster-affected counties. The economic significance of the effect is large. For example, using the number of disasters in a year as the measure of natural disasters, a one standard deviation increase in the indirect disaster exposure via social connections is associated with a $48,356 increase in deposits (0.56 percentage point increase in deposit growth), which is about 2.3% of the average deposits (20% of the average deposit growth) in the counties in our sample. These results are not driven by counties that are more disaster-prone and are robust to controlling for cross-county migration that may affect the intensity of social connections over time.

For the purpose of our study, it is critical to examine whether the mechanism behind our findings on county-level bank deposits is indeed social connections, and so we conduct several exercises to reinforce the social connections mechanism. First, we show that alternative measures of indirect disaster exposure that do not use the granular SCI value do not affect deposits, which means that the detailed information on social connections included in our measure is critical in explaining county-level deposit demand. Second, we show that our findings are not driven by disasters that cause large amounts of monetary damage, which households are likely aware of through other channels, such as traditional news media. This suggests that social connections transmit smaller shocks that aggregate up to have a meaningful effect on county-level deposit demand. Third, we rule out the possibility that our results are due to channels that arise from other types of cross-county linkages, such as multimarket bank branch networks, population migration, economic connections, or depositors who reside close to county borders.

The results on county-level deposits support our hypothesis that depositors' social connections have a meaningful impact on bank deposits. In the final part of the paper, we explore the implications for deposit funding at the overall bank level. First, we confirm that social connections play an important role in transmitting shocks that have a bank-wide impact: if a bank collects more deposits in counties that are more connected to disaster-affected areas, it experiences a significant increase in overall deposit levels and growth. Second, we examine the relation between social connections and bank deposits outside the context of natural disasters. We find that banks that take deposits from highly socially-connected counties have a higher level of deposit volatility, suggesting that high social connectedness exposes banks to greater deposit funding risk. Finally, we show that geographic diversification may mitigate the funding risk associated with depositors' high social connectedness: banks with more geographically dispersed branches experience a smaller increase in the deposit volatility that is associated with depositors' social connectedness.

Overall, our paper provides novel evidence that social connections have a meaningful effect on the most important aspect of banks' value creation—deposit collecting (Egan, Lewellen, and Sunderam (2022)). In particular, social connections transmit shocks, including small shocks, that can aggregate up to have a significant impact on deposits and deposit funding stability. Our findings, therefore, suggest that depositors' social connections should be an important consideration in banks' operations and risk management. Additionally, we show that geographic diversification is one way for banks operating in highly socially-connected counties to maintain deposit funding stability.

The remainder of this paper is structured as follows. In Section 2 we review the related literature, in Section 3 we describe the data, in Section 4 we present the main county-level empirical specification and results, in Section 5 we address and rule out alternative explanations, in Section 6 we investigate the implications at the bank level, and in Section 7 we conclude.

2 Related Literature

Our results relate and contribute to multiple strands of literature. First, we contribute to the literature on the determinants of bank deposits and deposit stability. Earlier work by Becker (2007) documents that the fraction of senior population is positively associated with the volume of bank deposits. More recently, Drechsler, Savov, and Schnabl (2017) show that local bank deposit market power increases banks' deposit outflows when the Fed Funds rate increases, and Li, Loutskina, and Strahan (2021) show that deposit market power reduces bank funding risk, enabling them to originate long-term loans. Lin (2020) provides evidence that households' demand for retail deposits decreases during stock market booms, and Choudhary and Limodio (2021) show that bank deposit volatility has important real effects on firms. We add to this literature by showing that depositors' social connectedness is an important determinant of bank deposits and deposit funding stability.

Second, we contribute to the literature on the impact of social connections on financial decisions. Prior literature provides evidence that social connections influence a variety of individual financial decisions, including stock-market participation (Hong, Kubik, and Stein (2004a) and Brown, Ivkovic, Smith, and Weisbenner (2008)), renting versus owning a house (Bailey, Cao, Kuchler, and Stroebel (2018a)), mortgage leverage (Bailey, Davila, Kuchler, and Stroebel (2019)), and the purchase of flood insurance (Hu (2022)).[4] However, as pointed out in Kuchler and Stroebel (2020), there is limited empirical evidence on how individual behavior influenced by social connections affects *aggregate* outcomes. Kuchler, Li, Peng, Stroebel, and Zhou (2022) make progress on this issue by documenting that social connections influence firms' access to institutional capital. Our findings, therefore, add to this literature by showing that social connections can transmit shocks, including small ones, which aggregate up to have a meaningful effect on funding to the banking sector.

[4]The literature also shows that social connections can impact investment decisions made by professionals. For example, Hong, Kubik, and Stein (2004b) provide evidence that mutual fund managers are more likely to transact in a stock if other managers in the same city do, which suggests that word-of-mouth communication impacts stock purchases and sales.

Third, we contribute to the literature on the impact of natural disasters on the banking industry. This literature evaluates how banks adjust their operations following such disasters, including mortgage and small business lending (Garmaise and Moskowitz (2009) and Chavaz (2016)), and lending to facilitate the recovery of disaster-affected areas or firms (Cortes (2014), Koetter, Noth, and Rehbein (2020), Rehbein and Ongena (2021), and Brown, Gustafson, and Ivanov (2021)). In particular, Cortes and Strahan (2017) use data on natural disasters and find that multi-market banks contract lending in markets that are unaffected by disaster and reallocate credit to the affected markets. Our findings, together with Cortes and Strahan (2017), point out the important spillover effect of natural disasters on bank operations. However, our finding is distinct from the effects of bank branch networks documented in Cortes and Strahan (2017), as our study highlights the role of social connections in transmitting shocks that influence bank operations.

Fourth, we contribute to the literature on the impact of background risks on precautionary saving motive. A number of papers focus on precautionary saving and the impact of future uncertainty along a variety of dimensions on the motive to save. Leland (1968), Sandmo (1970), Dreze and Modigliani (1972), Kimball (1990), and other subsequent work[5] focuses on uncertainty in future labor income, future interest rates, or both as drivers of current period savings. The precautionary savings motive is also closely related to the literature on "background risk," which considers uncertainty of more than labor income or interest rates (e.g., Eeckhoudt, Gollier, and Schlesinger (1996), Courbage and Rey (2007), and Eeckhoudt, Rey, and Schlesinger (2007)). This literature considers risks such as environmental risk or health risk that are not *directly* tied to wealth and that thus exist in the background of household savings decisions. Our study contributes to this strand of literature by demonstrating the role of social connections in influencing households' precautionary savings behavior. In our study, natural disasters that occur in other counties impose both significant background risks and uncertainty in the future, if there is a high degree of social

[5]See Baiardi, Magnani, and Menegatti (2020) for a survey of the precautionary saving literature.

connectedness to the disaster-affected counties.

Finally, closely related to our study are two contemporaneous papers that also use SCI data to study the effects of social connections on banks. Rehbein and Rother (2022) show that cross-county bank lending increases with social connectedness, and Cramer and Koont (2021) show that social connections can influence households' choice of where they bank through peer effects. Different from these papers, we study whether social connections influence deposits through a precautionary saving channel, and our focus is on the level and growth of deposits, rather than on where those deposits are made within a county. Our paper, together with these two papers, provides evidence that social connections have a meaningful impact on banks' operations.

3 Data

We obtain data on natural disasters from the Spatial Hazard Events and Losses Database for the United States (SHELDUS).[6] This database contains measures of multiple types of natural disasters and "perils," including thunderstorms, hurricanes, floods, wildfires, tornadoes, flash floods, and heavy rainfall. We include all types of disasters in our analysis, and we aggregate the SHELDUS data, which is originally reported at the county-month level, to either the county-quarter or county-year level depending on the type of analysis.

We construct two measures of the frequency of natural disasters. The first measure, $Disaster(n)$, is equal to the number of disaster records in a county-time period. The second measure, $Disaster(m)$, is equal to the number of months in a given time span for which disasters result in above-median damage (property and crop damage).[7] The "above-median" cutoff point ensures this measure includes nontrivial natural disasters.

Panel A of Table 1 reports summary statistics for disaster and disaster exposure variables.

[6] See `https://cemhs.asu.edu/sheldus` for further information.

[7] As an example of how these two measures are constructed at the yearly level, assume County A experiences 1 disaster per month in year t, and that the disasters in January, February, and March all result in above-median damage. Then in this case, $Disaster(n)$ is equal to 12 and $Disaster(m)$ is equal to 3.

The average county experiences nearly five disasters per year (*Disaster(n)*) and experiences 1.2 months per year with above-median disaster damages (*Disaster(m)*).

To compute the strength of social connections, we use the SCI available from Facebook, which is based on the measure constructed in Bailey, Cao, Kuchler, Stroebel, and Wong (2018b). This measure of social connectedness between counties is equal to the number of Facebook connections between users in county i and county j, scaled by the product of the total number of Facebook users in each county:

$$Social\ Connectedness_{i,j} = \frac{connection_{i,j}}{user_i \times user_j}.$$

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 value available to us lies between 1 and 1 billion.[8] SCI reflects the relative probability of a Facebook friendship link between two counties, and thus gives us pairwise social connectedness measures for each county pair.[9] Importantly, the SCI is not designed to capture literal Facebook interactions, such as posting news articles or exchanging messages. Similar to the existing literature that uses the SCI data (see, e.g., Kuchler, Li, Peng, Stroebel, and Zhou (2022) and Hu (2022)), we use it to proxy for unobservable real-world friendships and social connections, rather than online social media activity. 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 (i.e., Duggan, Ellison, Lampe, Lenhart, and Madden (2015)). Nonetheless, we conduct a robustness test to confirm that

[8] See the methodology description at `https://dataforgood.facebook.com/dfg/docs/methodology-social-connectedness-index` for more details, including details on other steps taken by the data providers to protect user privacy. For access to the data, see `https://dataforgood.fb.com/` and `https://data.humdata.org/dataset/social-connectedness-index`.

[9] Because the SCI value available to us lies between 1 and 1 billion, before using the data in our study, we first divide the SCI value in the dataset available to us by 1 billion in order to convert it into a weight. This weight represents the probability of connections between a pair of given counties relative to the probability of connections between the pair of counties with the highest overall social connectedness in the sample.

our results are not sensitive to unobserved time variation in social connections that arises due to population migration.[10]

For the county-level analysis, our deposit data comes from the Federal Deposit Insurance Corporation's (FDIC) annual Summary of Deposits (SOD). This summary is produced annually at various levels of geographic disaggregation and covers the period from July of the previous year to June of the current year. Using this dataset, we compute both deposit levels and deposit growth rates for each county. Because social connections are measured using friend connections in Facebook, which opened to the public in September 2006, we restrict our analysis to 2007-2019. Panel A of Table 1 reports that, on average, counties in our sample have roughly \$2 million in deposits and experience 2.9 percentage point growth in deposits annually. The SOD data also provides information that allows us to calculate the geographic diversification of bank deposits.

For the bank-level analysis, we collect deposits from the quarterly Federal Financial Institutions Examination Council's (FFIEC) Call Reports. We also construct additional quarterly control variables using the Call Report data following Lin (2020): equity ratio (the equity-to-assets ratio equal to data series $RCON3210$ divided by $RCON2170$), bank size (equal to the natural log of assets), and income ratio (the income-to-assets ratio equal to data series $RIAD4330$ divided by lagged assets). Summary statistics for these variables are reported in Panel B of Table 1.

County GDP and population are from the Bureau of Economic Analysis. We use the NBER County Distance Database to compute geographic distance between counties. Migration data are from the Census Bureau's American Community Survey (ACS).

[10]See Section 4.2 for details.

4 Indirect disaster exposure and county-level deposits

4.1 Variables and regression model

Our primary explanatory variable is *Social Proximity to Disaster* (which we abbreviate as *Social proximity* in the tables), which is county i's indirect disaster exposure via social connections at time t. This variable is computed as:

$$Social\,Proximity\,to\,Disaster_{i,t} = \sum_{j=1}^{N} SCI_{i,j} \times Disaster_{j,t},$$

where $SCI_{i,j}$ is the SCI value between counties i and j (the SCI value described in the previous section), and $Disaster_{j,t}$ is either $Disaster(n)$ or $Disaster(m)$ for county j at time t.

We use *Social Proximity to Disaster* as our primary explanatory variable in the following regression:

$$\begin{aligned} Y_{i,t} &= Social\,Proximity\,to\,Disaster_{i,t-1} + Disaster_{i,t-1} \\ &+ Geographic\,Proximity\,to\,Disaster_{i,t-1} + Ctrls_{i,t-1} + c_i + y_t + \epsilon_{i,t}, \end{aligned} \tag{1}$$

where $Y_{i,t}$ is the dependent variable of interest. Depending on the specification, we use either levels or growth rates of deposits as the dependent variable. In all specifications, the independent variables are lagged one year relative to the dependent variable.

The variable *Disaster* is a measure of natural disasters that occur in the focal county i. To control for the focal county's physical distance to disasters in other counties, we define *Geographic Proximity to Disaster* (abbreviated as *Geographic proximity* in the tables) as the geographic distance-weighted indirect disaster exposure for county i, computed as

$$Geographic\,Proximity\,to\,Disaster_{i,t} = \sum_{j=1}^{N} Distance_{i,j} \times Disaster_{j,t},$$

where $Distance_{i,j}$ is the inverse of the distance between counties i and j scaled by the largest distance in the sample.[11]

$Ctrls$ is a set of county macroeconomic controls: GDP per capita and population when the dependent variable is deposit amount, and the percentage growth in GDP and population when the dependent variable is deposit growth.[12] c_i and y_t are county and time fixed effects, respectively. Because deposits in the FDIC SOD data are reported for the period between July of the previous year and June of the current year, we line up the timing by computing $Social\,Proximity\,to\,Disaster_{i,t}$ from July of $t-1$ to June of t. All independent variables are lagged one period relative to the dependent variable.

Our identification strategy relies on the variable *Social Proximity to Disaster*, which takes into account (1) disasters that occur in all other counties, and (2) the social connections between the focal county and all other counties. This variable captures the extent to which the deposit decisions of households in a county could be influenced by natural disasters that occur in other counties through social connections.

The identifying assumption is that *Social Proximity to Disaster* is exogenous to the focal county's bank deposits after accounting for both fixed- and time-varying county characteristics, as well as fixed time effects. This assumption is highly plausible, and we do not expect the results to be confounded by either reverse causality or omitted variable bias.

In order for reverse causality to be a concern, the focal county's deposits would have to drive either natural disasters in all other counties, or social connections between the focal county and all other counties, or both. It is inconceivable that the focal county's deposits would determine natural disasters in other counties. Furthermore, it is highly unlikely that the focal county's deposits would determine the intensity of social connections between coun-

[11]We obtain data on the geographic distance between counties from the NBER's County Distance Database (`https://www.nber.org/research/data/county-distance-database`).

[12]Bailey, Cao, Kuchler, Stroebel, and Wong (2018b) show that social connections are related to economic linkages such as trade flows, migration, and innovation. The inclusion of county-level macroeconomic controls, such as GDP, should partially alleviate concerns that we are picking up an effect of economic linkages. This is because changes in, e.g., cross-county trade or innovation that occur as a result of natural disasters should be reflected in changes in county GDP. In Section 5 we further address concerns that our social connections measure simply proxies for economic linkages that transmit disaster shocks.

ties, because the SCI captures persistent social connections that are largely stable over time, whereas deposits are time-varying. More importantly, it is difficult to conceive a theoretical link between deposits and the focal county's social connections with every other county in the U.S. In order for omitted variables to be a concern, unobserved factors would have to simultaneously determine natural disasters in all other counties, the focal county's social connections with every other county, and the focal county's bank deposits. The time-varying and fixed county and time characteristics we include in equation 1 account for such factors.

4.2 Results

Table 1 Panel A summarizes the county-level data, and Table 2 reports the results of estimating equation 1. The independent variable of interest is the lagged *Social Proximity to Disaster* using the two measures of disasters, denoted as *Social proximity(n)* and *Social proximity(m)*, respectively. In columns 1-2 and 5-6 the dependent variable is the level of deposits, and in columns 3-4 and 7-8 the dependent variable is deposit growth (percentage change in deposits from the previous year). For macro controls, in columns 1-2 and 5-6 we use one-year lagged county GDP per capita and population, and in columns 3-4 and 7-8 we use percentage change in county GDP and population. Finally, columns 1-4 include county and year fixed effects, whereas columns 5-8 include county and state×year fixed effects. The inclusion of state×year fixed effects allows us to account for time-varying location specific unobserved factors, such as changes in state laws and regulations, that may be correlated with both deposits and social connectedness.[13]

The coefficients on the *Social proximity* variables are positive and significant across all specifications. This suggests that stronger social connections to disaster-affected counties result in an increase in deposit amount and growth, holding constant geographic distance. The results imply large economic significance. For example, using the number of disasters in a year as the measure of natural disasters, a one standard deviation increase in *Social*

[13] We include this level of fixed effect to establish the robustness of our baseline result and only include county and year fixed effects in the subsequent analysis.

proximity(n) is associated with a \$48,356 increase in deposit amount, which is about 2.3% of average deposits in a county-year; the same increase in *Social proximity(n)* is associated with a 0.56 percentage point increase in deposit growth, which is about 20% of average deposit growth in a county-year.

Because equation 1 is estimated at the annual frequency (due to the fact that county deposit data is only available at an annual frequency), our results suggest that the indirect impact of disasters on deposits in socially connected counties does not dissipate or reverse after a few months. This effect is, therefore, more persistent compared with the results in previous papers that show disasters have a more transient, short-term impact on bank *lending* in directly affected areas (see, e.g., Garmaise and Moskowitz (2009), Cortes (2014), and Cortes and Strahan (2017)). This longer-term effect on deposits is consistent, though, with the contemporaneous work of Kundu, Park, and Vats (2022), who find that disasters have a permanent impact on deposit growth in impacted areas. Our finding is also in line with the prior literature, which documents that disasters are likely to have a long-term impact on individuals (e.g., Bernile, Bhagwat, and Rau (2017)) and Hudson, Botzen, Poussin, and Aerts (2019)). Therefore, our results, along with those of Kundu, Park, and Vats (2022), suggest that deposits, which are largely determined by households, respond to shocks induced by natural disasters differently than loans, which are primarily determined by financial institutions.

The coefficients on *Geographic proximity* are largely insignificant, but the primarily negative signs are consistent with greater distance from disaster-affected counties being associated with a smaller increase in precautionary savings. The coefficients on *Disaster* are mostly negative and significant, which is consistent with a draw down of deposits by households that are directly affected to support disaster recovery. The variable *Disaster* includes only disasters from the preceding year. To alleviate concerns that counties with a history of experiencing many natural disasters respond differently from counties in which disasters occur infrequently, in Appendix A.1 we include a control variable for whether a county is disaster prone. The results, reported in Table A.2, show that the effects of *Social Proximity to Disaster* are not driven by disaster-prone areas.

The SCI used in this study is constructed using the August 2020 snapshot of Facebook connections. Using a snapshot of SCI is appropriate because SCI is not volatile according to Facebook data scientists, and thus should capture persistent social connections that are largely stable over time. Nonetheless, it remains important to understand whether and to what extent counties that experience high migration (either into or out of the county) may influence our main findings. To investigate this issue, we reestimate our baseline county-level deposit analysis after removing counties with high net migration.

To measure migration across county pairs, we use the net migration data from the Census Bureau's American Community Survey (ACS) migration data. The ACS migration data is published for rolling five year time spans beginning with the 2007-2011 time period.[14] Because 2011 is the earliest year for which we have data, we conduct our robustness analysis for the 2011-2019 subset of our sample.

For each county pair in each year, we construct a variable equal to the net migration between the counties scaled by the average population of the two counties. For two counties A and B, net migration is equal to (the absolute value of) migration from A to B minus migration from B to A. We compute the net migration for each county pair during 2011-2019 and define counties with net migration over the 90th percentile over the sample period as high net migration county pairs. Then, to conduct our robustness analysis, we recompute the *Social Proximity to Disaster* for each focal county by excluding any other county for which the net migration between that other county and the focal county is above the 90th percentile. For example, assume there are three counties (A, B, and C) and that net migration between A and B is in the 50th percentile, whereas net migration between A and C is in the 96th percentile. In this example, when we recompute the *Social Proximity to Disaster* for county

[14]The ACS is "the premier source for detailed population and housing information" (see `https://www.census.gov/programs-surveys/acs` for more information). The ACS publishes other migration datasets beginning in earlier five year windows, but the county-to-county net migration data is only available beginning with the 2007-2011 period.

A, we only consider disasters in county B but exclude those in county C.[15]

The results of reestimating our primary county-level deposit analysis after recomputing the *Social Proximity to Disaster* are reported in Table 3. We label our main independent variables using "ex-high migration" to denote the fact that we exclude the high net migration county pairs. Both measures of *Social proximity ex-high migration* are positive and significant for deposit amount and growth, indicating that our primary results are not sensitive to the exclusion of high net migration county pairs. Therefore, it is unlikely that our results are sensitive to unobserved time variation in the strength of social connections that arises due to migration between counties.

5 Indirect disaster exposure and county-level deposits: social connections as the underlying mechanism

The previous section shows that social connections transmit shocks that affect deposits. In this section, we explore whether the mechanism behind our county-level results is indeed social connections. We explore this issue from three angles. First, we investigate how important the granular information on social connections contained in *Social Proximity to Disaster* is in driving our main results. Second, we examine whether *Social Proximity to Disaster* simply captures the effects of large disasters that depositors are likely aware of through traditional news media, and not necessarily through their social connections. Third, we examine three alternative channels, which could arise from other cross-county connections, that may explain our main results.

[15]Note that we do not exclude any counties from the computation of the *Geographic Proximity to Disasters* variable given that net migration should have no impact on how physical distance mediates the precautionary savings motive.

5.1 The importance of the granular information incorporated in *Social Proximity to Disaster*

If the mechanism behind our county-level results is indeed social connections, then the detailed information about social connections incorporated in *Social Proximity to Disaster* should drive our main results. To investigate whether this is the case, we explore two issues.

First, we investigate if *Social Proximity to Disaster* simply captures a county's exposure to disasters through a few of its most connected counties, regardless of the intensity of the connections. We do this by examining whether an alternative measure of indirect disaster exposure that is not based on the exact SCI value performs equally as well as *Social Proximity to Disaster* in explaining changes in deposits. Specifically, for each focal county we choose the top ten connected counties based on SCI. We create two measures to capture a focal county's exposure to disasters in these ten counties. First, we compute the raw (unweighted) average of the disaster measures across the top ten counties in the given year, and call this variable *Unweighted Social Proximity to Disaster (Top 10)* (abbreviated as *Unweighted social proximity (top 10)* in the tables).[16] Second, we compute the SCI value-weighted disasters in the top ten connected counties, and call this variable *Social Proximity to Disaster (Top 10)* (abbreviated as *Social proximity (top 10)* in the tables). We then compare the impact of these two measures on deposits in the focal county.

The results are reported in the top panel of Table 4. In columns 1-4 we regress the level or growth rate of deposits on *Social proximity (top 10)*, whereas in columns 5-8 we regress the level or growth rate of deposits on *Unweighted social proximity (top 10).* We find that *Social proximity (top 10)* in columns 1-4 loads positive and significant for deposits, indicating that disasters in the top 10 most connected counties play a significant role in influencing households' deposits in the focal county, which is consistent with the findings for all counties in Table 2. In contrast, *Unweighted social proximity (top 10)* in columns 5-8 does not tell a

[16] As an example, if there are an average of 25 disasters in a given year across the top ten counties, the unweighted disaster exposure based on the number of disasters is 25.

clear story. The coefficients on the unweighted measures have contradicting signs when the dependent variables are the level of deposits and the growth rate of deposits, respectively. Given the lack of clear direction using the unweighted measures, this table suggests that the SCI values are critical in capturing how social connections mediate households' precautionary savings motives and influence bank deposits. The results are qualitatively the same if we use the top 20 or 50 most connected counties.

Second, we investigate whether the value of SCI contains information beyond the rank-ordering established by the index. As an example of the difference between the value of the index and the ranking established by the index, consider comparing two sets of counties. Set 1 contains counties A, B, and C, and Set 2 contains counties D, E, and F. Assume that County A is most strongly connected to B, followed by C, and assume that County D is most strongly connected to E, followed by F. Finally, assume that the value of SCI between A and B is 100, whereas the value between D and E is 10. If only the rank-ordering matters, then the impact of a disaster in County B on County A should be similar to the impact of a disaster in County E on County D. If instead the SCI value matters incrementally with respect to the rank-ordering, then the impact of a disaster in B on A should be stronger than the impact of a disaster in E on D.

To investigate this issue, for each focal county we create *Social Proximity to Disaster (Rank Only)* (abbreviated as *Social proximity (rank only)* in the tables), which weights disasters in other counties by the inverse of their ranks in SCI, rather than by the value of SCI.[17] The results are reported in the bottom panel of Table 4. The rank-based indirect disaster exposure is insignificant in all four specifications, which suggests that the detailed value of SCI provides information beyond a simple rank-ordering.

Overall, Table 4 suggests that the granular SCI value, which reflects detailed information on the intensity of social connections, is important in understanding the effects of social

[17]As an example, assume County A is connected to Counties B and C and that the value of the SCI between A and B is 100, whereas the SCI between A and C is 50. Then B ranks higher than C based on SCI. Thus, instead of multiplying the disaster measures by 100 (for B) and 50 (for C), we multiply the measures by 1 for B and $\frac{1}{2}$ for C (since the rank of B is 1 and the rank of C is 2).

connections on county-level deposits. This evidence, therefore, supports social connections as the underlying mechanism of our findings.

5.2 Disaster frequency v.s. monetary impact

In creating our key variable *Social Proximity to Disaster*, we utilize information on the frequency of natural disasters, rather than the dollar amount of damage caused by disasters. We do so for two reasons, both related to the mechanism through which social connections may influence households' deposit demand. First, the frequency of disasters should be positively associated with the number of people directly affected by the disasters, and as more people are affected, these disasters are likely to influence the deposit behavior of more people in other counties through social connections. For example, if a greater number of natural disasters occur in County A in a year, these disasters are likely to impact more households in that county. As a result, a greater number of households in other counties are likely made aware of the disasters that occurred in County A through social connections, leading to a greater increase in their precautionary saving incentive and ultimately bank deposits. In contrast, if a smaller number of natural disasters occur in County B in the same year, these disasters are likely to impact fewer households, even if the amount of monetary damage caused is the same as the amount in County A. As a result, a smaller number of households in other counties are likely made aware of the disasters in County B, leading to a smaller change in bank deposits.

Second, large disasters that cause severe damage are likely to be known to households in other counties through channels other than, or in addition to, social connections. For example, the wildfires in California in 2020 or Hurricane Ida in 2021 are likely known across all U.S. households through traditional media outlets. Therefore, it is not appropriate to attribute the change in household deposits following those severe disasters only to social connections.

If social connections influence bank deposits through the mechanism we propose, the frequency of disasters (regardless of size) should have explanatory power for deposits even after controlling for the occurrence of very damaging disasters. To examine whether this is the case, we modify our baseline specification by adding a control for the occurrence of large damage caused by natural disasters. Specifically, for each county-year, we define an indicator equal to 1 if the dollar amount of damage across all disasters is in the 75th percentile or above, and 0 otherwise. We then create the variable *Social Proximity to Disaster (Dollar Damage* (abbreviated as *Social proximity (dollar damage)* in the tables) by weighting the large damage indicator by the SCI value.

The results are reported in Table 5. For both deposit amount and growth, *Social proximity (dollar damage)* is positive and significant, and the effect is economically large. This is consistent with highly damaging disasters being more visible than smaller disasters, and hence inducing a large increase in the demand for deposits. Despite this, our main variable *Social proximity* remains significant, indicating that the frequency of disasters provides important information for deposits even when we control for indirect exposure to high levels of monetary damage. In other words, our finding is not driven by disasters that cause large damage. These results, therefore, further support that social connections are likely to be the mechanism driving changes in county-level deposits.

Table 5 also highlights a key advantage of our study: the ability to capture changes driven by small, less publicized shocks to depositors' precautionary saving motive. The fact that *Social proximity* remains significant after controlling for large (and likely well-known) disasters indicates that social connections transmit smaller shocks. Although small shocks may not have an economically meaningful effect individually, in aggregate they may be meaningful. Consider the marginal effects of *Social proximity(n)* and *Social proximity (dollar damage)* in column 1. A one standard deviation increase in *Social proximity(n)* results in an increase in deposit levels of 1.4% relative to the mean, whereas the same increase in *Social proximity (dollar damage)* results in an increase of 1.6% relative to the mean. In terms of deposit growth, the marginal effect, relative to the mean, of a one standard deviation increase in *Social proximity(n)* is roughly a third as large as the same increase in *Social proximity (dollar damage)* (7% vs 22%). Overall, though, the aggregate impact of small shocks transmitted via social connections on county-wide deposits is still meaningful relative to the impact of large shocks.

5.3 Alternative channels

Social connections are not random and are likely correlated with other cross-county connections. As a final approach to showing that social connections are the mechanism driving our results, in this section we undertake four exercises to address concerns that our results are driven by other cross-county connections, such as financial market or economic linkages, rather than social connections. That is, we address concerns that natural disasters exogenously impact deposits in unaffected counties due to presence of cross-county connections that are *not* social in nature.

5.3.1 Multimarket bank branch networks

One important type of cross-county connection that is not social in nature is a financial market connection through bank branch networks. Recent work by Cortes and Strahan (2017) show that multimarket banks increase deposit rates in counties unaffected by natural disasters in order to attract more deposit funding, and subsequently funnel that funding into disaster-affected markets in which loan demand has increased. If this is the case, then our main results may be primarily driven by multimarket banks' incentive to reallocate funds, rather than changes in precautionary saving incentives that are induced by social connections.

To examine whether our results are primarily due to the reallocation of funds across branches by multimarket banks, we re-estimate our county-level deposit regression by focusing only on disasters in counties that do not have any depository institutions that operate in the focal county as well. Because there is no overlap in banks between the focal county and the disaster-affected counties, this empirical strategy eliminates the possibility that branches in the focal county increase interest rates in order to attract deposits which can then be allocated to branches in the disaster-affected counties.

We conduct this exercise by first identifying, for each focal county i, all other counties j for which at least one bank b in i has a branch in j. We then recompute *Social Proximity to Disaster* by excluding disasters in counties that share at least one bank with the focal county. We do so by setting the disaster measures to 0 in our computation of *Social Proximity to Disaster* when there is bank overlap, such that, when counties i and j share a bank, disasters in j do not add to i's SCI-weighted-average disaster exposure. The result is a new variable called *Social Proximity to Disaster - no bank overlap* (abbreviated *Social proximity - no bank overlap* in the table) that incorporates only disasters in counties for which there is no overlap in depository institutions.

The results are reported in Table 6. After accounting for the potential impact of bank branch networks on deposits, the new version of our main variable of interest, *Social Proximity to Disaster - no bank overlap*, is positive and significant for county-level deposit amount (columns 1-2) and growth (columns 3-4). These results indicate that even when counties do not share banks, disasters in one county result in increased deposits in the other county to a greater extent when social connections between the two are stronger. This evidence supports that social connections, rather than multimarket bank branch networks, are the underlying mechanism behind our main results.

5.3.2 Migration patterns

Counties may be more socially connected if there is more population migration between them. As Bailey, Cao, Kuchler, Stroebel, and Wong (2018b) show, the SCI between two counties is positively related to migration between those counties. Therefore, the second alternative cross-county connection that we consider is population migration across counties. Because intercounty migration could change the number and composition of depositors in a given county, the impact of *Social Proximity to Disaster* could be the result of a change in the focal county depositor base, rather than a change in precautionary saving motive of *existing* depositors. This potential alternative explanation is particularly important if households in disaster-affected areas tend to migrate to counties where they have social connections when they experience disasters.

To investigate whether our main results are due to this type of connection, which could have a direct economic impact on bank deposits, rather than social connections, we reestimate our county-level deposit analysis with the addition of two control variables that are constructed using the Census ACS data. The first variable directly addresses the possibility that households in disaster-impacted counties migrate into a given focal county because of the strength of their social connections with households in the focal county. This is important to account for because migration inflows from disaster-impacted counties could change the number of depositors in the focal county, and hence drive increases in deposit amounts and growth rates, even if households that already reside in the focal county do not change their precautionary saving behavior. We call this variable *Disaster-Weighted Migration* into county i in year t, computed as

$$Disaster - Weighted\ Migration_{i,t} = \sum_{j=1}^{N} Migration\ inflow_{i,j,t} \times I(Disaster)_{j,t},$$

where $Migration\ inflow_{i,j,t}$ is the migration inflow from county j to county i in year t scaled by the average population of i and j, and $I(Disaster)_{j,t}$ is an indicator equal to 1 if county j experienced any disaster in year t, and 0 otherwise. Because this variable is non-zero only when a disaster occurs in county j, it captures migration into county i that occurs in the same year as a disaster in j. Although such migration is not necessarily caused by the disaster in j, by conditioning on the disaster in j we can rule out migration inflows from *unaffected* counties, which are not driven by disasters.

In addition to $Disaster-Weighted\ Migration$, we create another variable *Net Migration* that is equal to average net migration in county i in year t. Unlike the disaster-weighted migration inflows variable, this variable captures overall migration, which may or may not be driven by inflows from disaster-impacted counties. Thus, this variable captures overall changes in county population, and hence changes in the number of households making deposits, that are not driven by, e.g., births within the county.

We report the results of estimating equation 1 using both these additional controls in Table 7. In columns 1-2, the migration controls are in levels, whereas in columns 3-4 they are both percentage changes. Our main variable of interest, *Social Proximity to Disaster*, remains positive and significant in three of the four specifications, which indicates that changes in migration driven by social connections to disaster-affected counties, as well as overall migration flows, do not significantly impact our main results. Therefore, it is unlikely that our main finding is driven by a correlation between social connections and migration patterns.

5.3.3 County economic connections

Social connections among counties are likely correlated with economic connections. To account for the possibility that economic connections among counties may explain our results, we create a variable that captures a county's exposure to disasters via its economic connections to disaster-affected counties. Our proxy for economic connectedness is based on the similarity in industry composition between two given counties. If two counties have similar industrial compositions, then economic linkages between them are likely to be strong. This is because their labor market dynamics may be closely linked and the firms located in them may have more trade relations. Existing economic connections such as these make it possible for location-specific shocks, such as the natural disasters we use, to induce workers to migrate from one county to another, or to induce changes in demand for goods and services produced in a county, both of which can influence deposits. As an example, assume that the manufacturing sector comprises the bulk of total employment in two counties, and that a natural disaster destroys a large manufacturing plant in one of the counties. If this occurs, then workers might migrate from the affected county into the unaffected county in hopes of finding a job. Alternatively, firms that previously purchased goods from the affected manufacturing plant might shift their demand to the manufacturing firms in the unaffected county. In both cases, it is conceivable that the unaffected county could experience an increase in deposit demand that is related to the economic connections to the disaster-affected areas, not the precautionary saving motive of households.

We measure a county's industry composition using the number of employees by industry from the Bureau of Labor Statistics' (BLS) Quarterly Census of Employment and Wages. Specifically, for each county-year, we compute the share of total county employment in each 2-digit NAICS sector. We then calculate the cosine similarity of industry employment shares for each county pair in our sample in each year, which we call $IndSimil_{i,j,t}$. Finally, for each county-year, we compute the *Economic Proximity to Disaster* as the weighted average disaster measures between county i and all other counties, where the weights are industry cosine similarity:

$$Economic\,Proximity\,to\,Disaster_{i,t} = \sum_{j=1}^{N} IndSimil_{i,j,t} \times Disaster_{j,t},$$

The variable *Economic Proximity to Disaster* is higher when county i's industry composition is more similar to counties that experience more disasters.

We include *Economic Proximity to Disaster* (abbreviated as *Economic proximity* in the tables) in our baseline specification and report the results in Table 8. Our main variable of interest, *Social Proximity to Disaster*, remains positive and significant, whereas the *Economic proximity* variables are largely insignificant across specifications. The evidence, therefore, suggests that it is unlikely that our main finding is driven by a correlation between social connections and economic connections.

5.3.4 Disasters in bordering counties

The final cross-county connection that we consider is border sharing, which raises the possibility that our results are driven by depositors that reside close to the border of counties that are affected by disasters, despite not technically residing in an affected county. This is important because households that reside close to county borders might react to a disaster in the adjacent county primarily because of the close geographic proximity, rather than social connections. Additionally, if a household that resides in County A works in County B, they may also react to the disaster in County B given they spend a significant portion of their time in County B.

To determine whether this cross-county connection drives our results, we recompute *Social Proximity to Disaster* by removing, for each focal county, the top-10, top-20, top-50, or top-100 closest counties by geographic distance.[18] These new *Social proximity* variables therefore only use disaster information from geographically distant counties and eliminate the impact of nearby counties. We reestimate our baseline equation 1 using the new *Social proximity* variables and report the results in Table 9. Columns 1-4 (5-8) of the top panel remove the top 10 (top 20) closest counties, respectively, and columns 1-4 (5-8) of the bottom panel remove the top 50 (top 100), respectively. Regardless of the number of close counties we remove, *Social Proximity to Disaster* remains positive and significant for both the level of and growth in deposits. Therefore, our main results are unlikely due to depositors that reside close to the border of counties that are affected by disasters.

6 Implications for banks' deposit funding stability

Our results thus far show that county-level deposits are influenced by shocks experienced by households' social connections. In this section, we explore the implications of social connec-

[18]The average distances between a focal county and its top-10, top-20, top-50, and top-100 closest counties are 43 miles, 58 miles, 91 miles, and 130 miles, respectively.

tions for banks. In particular, we focus on bank deposit funding stability. Because social connections are important in transmitting shocks that influence deposits, it is possible that a bank's deposit stability is related to its depositors' social connectedness. Understanding the implication of depositors' social connectedness on bank deposit funding stability is important because deposits constitute the primary source of funding for banks,[19] and deposit stability is crucial for banks' ability to provide long-term credit, which is consequential for firms (see, e.g., Li, Loutskina, and Strahan (2021) and Choudhary and Limodio (2021)).

Households' social connections may experience various types of shocks. Some shocks may increase the tendency to save through deposits, while others may encourage a shift away from deposits.[20] As long as depositors' social connectedness is positively associated with the number and intensity of shocks to banks' deposit funding, greater social connectedness is likely to lead to greater deposit volatility. However, if social connections result in positive and negative shocks that offset one another, banks with more socially connected depositors may experience lower deposit volatility. As such, the average effect of depositors' social connectedness on banks' deposit stability is an open question.

We take three steps to address the relation between depositors' social connectedness and bank deposit funding stability. First, using natural disasters, we establish that shocks transmitted through county-level social connections aggregate up to influence deposit funding at the bank level. Second, we examine the association between depositors' overall social connectedness (unrelated to specific shocks such as natural disasters) and bank deposit volatility. Finally, motivated by the empirical literature on the impact of bank geographic diversification, we analyze the joint impact of social connectedness and geographic diversification on deposit funding stability.

[19] Hanson, Schleifer, Stein, and Vishny (2015) show that, in aggregate, the share of total bank liabilities comprised of deposits has consistently been around 75% over the past century.

[20] For example, Bailey, Davila, Kuchler, and Stroebel (2019) document that individuals with friends that experience high house price growth will be more optimistic about their future local house price growth, and subsequently take on less leverage. This adjustment in leverage might reduce households' deposits.

6.1 Indirect disaster exposure and bank-level deposits

To investigate whether shocks transmitted through social connections influence deposit funding at the bank level, we examine whether the increase in bank deposits at the county level due to households' indirect exposure to disasters translates to an increase in deposits for banks that have branches in the focal counties.

We first construct banks' indirect disaster exposure via social connection, which we call *Bank Social Proximity to Disaster* (abbreviated as *Bank social proximity* in the tables). This variable captures the extent to which a bank is impacted by its depositors' indirect exposure to natural disasters via social connections. This variable is the weighted average of the *Social Proximity to Disaster* of all counties in which the bank has branches, where the weights are the proportion of total bank deposits accounted for by the bank branches in a given county i. In other words, the more important a county i is to a bank's total deposits, the greater the weight county i receives.

Mathematically, we compute *Bank Social Proximity to Disaster* of bank b during time t as the following:

$$Bank\,Social\,Proximity\,to\,Disaster_{b,t} = \sum_{i=1}^{N} \frac{Deposit_{b,i,t-1}}{Total\,Deposit_{b,t-1}} \times Social\,Proximity\,to\,Disaster_{i,t}$$

$$= \omega_{i,b,t-1} Social\,Proximity\,to\,Disaster_{i,t},$$

where (b, i) constitutes a branch of bank b located in county i, and $Total\,Deposit$ is the sum of deposits across all branches of bank b. We lag the deposit weights one year so as not to contaminate the weight with the contemporaneous impact of the disaster exposure.

Consistent with the county-level analysis, to control for both direct disasters and the physical distance to disasters in other counties, we compute the following:

$$Bank\,Disaster_{b,t} = \omega_{i,b,t-1} Disaster_{i,t},$$

and

$$Bank\,Geographic\,Proximity\,to\,Disaster_{b,t} = \omega_{i,b,t-1} Geographic\,Proximity\,to\,Disaster_{i,t}.$$

After constructing these variables, we estimate the following equation[21]:

$$\begin{aligned} Y_{b,t} &= Bank\,Social\,Proximity\,to\,Disaster_{b,t-1} + Bank\,Disaster_{b,t-1} + \\ &Bank\,Geographic\,Proximity\,to\,Disaster_{b,t-1} + Ctrls_{b,t-1} + b_b + y_t + \epsilon_{b,t}, \end{aligned} \tag{2}$$

where the dependent variable $Y_{b,t}$ is the quarterly level of, or change in, deposits for each bank, b_b is a bank fixed effect, y_t is a quarter fixed effect, and $Ctrls$ is a set of bank-level controls: quarterly bank size, equity ratio, and income ratio (following Lin (2020)). Because the unit of observation for this exercise varies at the quarterly level, we construct *Bank Social Proximity to Disaster* based on quarterly county-level *Social Proximity to Disaster*.

Table 1 Panel B reports summary statistics for the bank variables, and Table 10 reports the regression results. The coefficients on *Bank social proximity* are positive and significant across specifications, indicating that bank-level deposits increase if the bank is more exposed to counties that are more socially connected to disaster-affected areas. Therefore, the results suggest that social connections play an important role in transmitting shocks that have a bank-wide impact.

6.2 Social connectedness and banks' deposit funding stability

Having established that the impact of county-level shocks aggregates up to the bank-level, we now examine the way in which depositors' social connectedness influences deposit funding stability. We measure the depositor social connectedness for a given bank based on the counties in which deposits are collected. We do so by computing the weighted average

[21] Banks with an *ex-ante* greater amount of deposits in a focal county are likely to experience a greater increase in deposits in the focal county following a disaster in a connected county. This is because depositors in the focal county should have no reason to change financial institutions after the disaster occurs in the connected county. This motivates the use of *Bank Social Proximity to Disaster* in the bank-level analysis.

county social connectedness for all counties in which a bank has branches. The weights are based on the time-varying ratio of a bank's deposits from a given county to its total deposits, therefore our depositor social connectedness measure is time-varying (at an annual frequency).

Specifically, we begin by computing the deposit ratio for bank b in county i in year t as

$$Deposit\,ratio_{b,i,t} = \frac{Deposit_{b,i,t}}{Total\ Deposit_{b,t}}.$$

We then define the average deposit ratio for bank b in year t ($Avg\,deposit\,ratio$) as the five-year rolling average deposit ratio computed over years $t-4$ to t. Finally, we multiply the average deposit ratio in a given year by the average SCI of county i ($Avg\,SCI$, which is equal to county i's average SCI value with all other counties), and then sum the product over each bank b. We call this measure Bank SCI:

$$Bank\,SCI_{b,t} = \sum_i Avg\,deposit\,ratio_{b,i,t} Avg\,SCI_i.$$

Using a panel of bank-year data, we then estimate the following regression:

$$Bank\,deposit\,vol_{b,t} = Bank\,SCI_{b,t} + Ctrls_{b,t} + b_b + y_t + \epsilon_{i,t}. \tag{3}$$

The dependent variable is deposit volatility for bank b in year t, which is computed as the five-year rolling standard deviation of deposits from $t-4$ to t, such that the period over which we compute $Avg\,deposit\,ratio$ is the same as the period over which deposit volatility is computed. The variables b_b and y_t are bank and year fixed effects. $Ctrls_{b,t}$ include bank size, equity ratio, income ratio, and bank deposit market power. Depending on the specification, we use either the continuous measure $Bank\,SCI$ or an indicator for high $Bank\,SCI$ (i.e., above the 75th percentile or above 90th percentile) as the main independent variable.

We control for bank deposit market power because Drechsler, Savov, and Schnabl (2017) and Li, Loutskina, and Strahan (2021) show that deposit market power is related to bank funding stability. To measure deposit market power, we follow Drechsler, Savov, and Schnabl (2017) and compute, for each bank-year, the weighted average bank branch HHI, where the weights are based on the contribution of county i to bank b's total deposits:

$$Bank\,HHI_{b,t} = \sum_{i} Deposit\,ratio_{b,i,t} \times Branch\,HHI_{i,t}. \tag{4}$$

Here, $Branch\,HHI_{i,t} = \sum_{b}(Deposit\,ratio_{b,i,t})^2$.

These variables are summarized at the annual frequency in Panel C of Table 1, and the regression results are reported in columns 1-3 in Table 11. In column 1 we use continuous $Bank\,SCI$, whereas in columns 2-3 we use indicators equal to 1 when $Bank\,SCI$ is greater than the 75th percentile or 90th percentile, respectively. Column 1 suggests there is not a linear association between depositors' social connectedness and bank deposit volatility. However, the result in column 3 suggests that when depositors' social connectedness is at the 90th percentile and above, bank deposit volatility increases significantly. This finding is consistent with a high degree of social connectedness exposing a bank to a greater number of shocks to deposits, thus increasing volatility and deposit funding risk. Our findings, therefore, imply that depositors' social connectedness, when it is very high, may impose significant risk for bank operations.

6.3 Social connectedness and banks' deposit funding stability: the role of geographic diversification

Given that banks with depositors with a very high degree of social connectedness tend to have higher deposit volatility, a natural question is whether this deposit funding risk can be mitigated. To investigate one potential way in which banks can offset the negative impact of depositor social connectedness, we focus on bank geographic diversification. This is motivated by the literature that illustrates how geographic diversification impacts bank operations. In particular, Goetz, Laeven, and Levine (2016) show that publicly-traded bank-holding companies with greater geographic diversification have lower exposure to idiosyncratic risk, and Levine, Lin, and Xie (2020) show that more geographically diversified banks have lower deposit funding costs. Although neither study directly addresses the link between funding stability and diversification, both suggest that diversification may reduce funding risk. Therefore, we posit that banks operating in highly socially-connected counties may be able to reduce their social-connection-related funding risk by increasing geographic diversification.

To examine whether geographic diversification mitigates the effect of social connectedness on funding stability, we follow Goetz, Laeven, and Levine (2016) to measure the degree of bank geographic diversification. Specifically, we first construct the yearly geographic deposit HHI ($GHHI_{b,t}$) of each bank across all counties i in which they operate:

$$GHHI_{b,t} = \sum_{i}^{N} (Deposit\, ratio_{b,i,t})^2. \tag{5}$$

We then construct an indicator variable $GeoDiv_{b,t}$ equal to 1 when bank b is geographically diversified (implying $GHHI_{b,t} < 1$), and 0 when bank b takes deposits from a single county and therefore has zero geographic diversification (implying $GHHI_{b,t} = 1$).

GeoDiv is summarized in Panel C of Table 1. Over 55% of the bank-year observations have some level of geographic diversification, which is broadly consistent with the finding in Kundu, Park, and Vats (2022) that 30% of bank deposits are concentrated in a single county and hence 70% are geographically diversified.[22]

We add *GeoDiv* as an additional independent variable in Equation 3 and also interact each Bank SCI variable with *GeoDiv*. The interaction terms capture the relation between high social connectedness and deposit volatility when a bank is geographically diversified. The inclusion of time-varying controls and bank fixed effects accounts for the fact that

[22]Kundu, Park, and Vats (2022) limit their analysis to banks with branches in at least 10 counties, which likely explains the difference between their results and ours.

observable and unobservable differences between single-county and geographically diversified banks (such as differences in business models) may be correlated with differences in deposit volatility between these two types of banks. The regression results are reported in columns 4-6 of Table 11. Across specifications, the interaction is negative and significant, indicating that banks that operate in multiple counties are exposed to less deposit volatility when their depositors are more socially connected. The results are qualitatively unchanged if we use the continuous measure $GHHI$ instead of the indicator variable $GeoDiv$.[23] This implies that more geographic diversification can offset the impact of high social connectedness on deposit funding volatility. In other words, for banks that operate in counties with a higher degree of social connectedness, one way to mitigate the effect of social connectedness on deposit stability is through geographic expansion.

7 Conclusion

We provide the first evidence that social connections can significantly influence bank deposit funding by affecting households' precautionary saving behavior. We find that counties that are more socially connected to a disaster-impacted county experience a significant increase in deposits, controlling for physical distance. We conduct numerous exercises to rule out alternative explanations and show that social connections are the underlying mechanism of our main finding.

Our findings have important implications for banks' funding stability. Because social connections transmit shocks that alter households' demand for deposits, banks that collect deposits in highly socially connected counties experience high deposit volatility. Therefore, our evidence suggests that depositors' social connectedness is an important operational risk factor for banks. Building upon prior literature, we show that banks can reduce the deposit volatility associated with depositors' social connections by diversifying their operations geographically.

[23]These results are available upon request.

Our findings also contribute to the social finance literature by providing evidence that social connections have a meaningful *aggregate* effect on capital markets through influencing households' saving behavior. The existing studies on social connections' impact on finance predominantly focus on documenting how these connections influence individual financial decisions. One exception is Kuchler, Li, Peng, Stroebel, and Zhou (2022) which provides evidence that social connections influence firms' access to equity capital from institutional investors. Our findings add to the literature by showing that social connections significantly affect bank deposit funding. Our findings therefore answer the call in Kuchler and Stroebel (2020) for empirical evidence on the effects of social connections on the aggregate quantities and prices of finance.

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Table 1: Summary statistics

variable	N	mean	p50	sd	min	max
Panel A: county-year observations						
County deposit amount ($1000)	40,465	2076.709	407.997	6497.599	16	48499.42
County deposit growth (%)	40,448	2.887	2.544	6.285	-17.897	27.872
Social proximity(n)	40,431	0.288	0.19	0.287	0.038	1.626
Social proximity(m)	40,431	0.08	0.045	0.096	0.007	0.564
Disaster(n)	40,314	5.142	3	6.464	0	34
Disaster(m)	40,314	1.247	1	1.536	0	7
Geographic proximity(n)	40,431	2.278	2.009	0.925	1.206	6.704
Geographic proximity(m)	40,431	0.529	0.472	0.219	0.279	1.602
GDP per capita ($million)	39,756	0.042	0.036	0.026	0.013	0.185
Population	39,756	90374.9	26122.5	192158.2	1230	1256016
GDP growth	39,769	0.033	0.032	0.088	-0.243	0.388
Population growth	39,756	0.002	0.001	0.012	-0.029	0.039
Social proximity ex-high migration(n)	27,988	0.278	0.185	0.273	0.037	1.54
Social proximity ex-high migration(m)	27,988	0.074	0.042	0.089	0.006	0.533
Unweighted social proximity(n)	40,431	4.784	3.5	4.237	0.1	21.1
Unweighted social proximity(m)	40,431	1.18	0.9	1.03	0	5
Social proximity(n) (rank only)	40,431	41.708	36.405	20.31	13.96	111.208
Social proximity(m) (rank only)	40,431	10.277	9.067	4.924	3.463	26.931
Social proximity (dollar damage)	40,431	0.036	0.022	0.04	0.003	0.248
Social proximity-no bank overlap(n)	40,418	0.13	0.066	0.176	0.008	1.059
Social proximity-no bank overlap(m)	40,418	0.039	0.017	0.062	0.002	0.394
Disaster-weighted migration	24,878	0.012	0.008	0.013	0	0.059
Net migration	22,394	0.006	0.005	0.011	-0.024	0.044
Economic proximity(n)	40,443	5721.452	5622.282	1918.738	931.618	13561.59
Economic proximity(m)	40,443	1371.218	1339.502	464.99	187.768	3104.787
Disprone	40,465	0.263	0	0.44	0	1
Panel B: bank-quarter observations						
Bank deposit amount ($1000)	342,900	531.608	140.024	1711.917	9.69	14229.07
Bank deposit growth (%)	342,176	0.015	0.008	0.059	-0.118	0.305
Bank social proximity(n)	343,342	0.054	0.028	0.072	0.004	0.428
Bank social proximity(m)	343,342	0.015	0.007	0.022	0.001	0.131
Bank size	341,340	12.161	12.027	1.33	4.22	21.221
Equity ratio	338,227	0.116	0.105	0.065	-2.15	1
Income ratio	340,263	0.005	0.004	0.032	-8.15	5.74
Panel C: bank-year observations						
Bank deposit vol	68,699	90.394	12.274	362.804	0.526	3059.879
Bank SCI	68,699	16568.53	11836.13	16338.35	1592.713	96275.66
Bank HHI	68,686	0.219	0.19	0.116	0.07	0.662
GeoDiv	68,699	0.561	1	0.496	0	1

Notes: 1) Panel A reports the summary statistics for county-year observations; Panel B reports the summary statistics for bank-quarter observations; Panel C reports the summary statistics for bank-year observations. Data is from SHELDUS, Call Reports, FDIC Summary of Deposits, BLS, and BEA, during the time period January 2007-July 2019. 2) All variables defined in Table A.1. 3) All variables winsorized at the 1% level in both tails.

Table 2: County-level deposits

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Deposit amount ($1000s)		Deposit growth (p.p.)		Deposit amount ($1000s)		Deposit growth (p.p.)	
Social proximity(n)	168.4863***		1.9653***		66.0181*		1.0003***	
	(37.8688)		(0.2846)		(39.8462)		(0.3350)	
Social proximity(m)		575.9601***		6.4404***		218.8511**		3.0453***
		(97.1560)		(0.8419)		(99.9333)		(0.9911)
Disaster(n)	-3.6761		-0.0128*		-0.8776		-0.0107	
	(3.0594)		(0.0076)		(2.8054)		(0.0074)	
Geographic proximity(n)	-63.9212		0.4674**		21.1959		1.4099	
	(61.7162)		(0.2051)		(136.8243)		(0.8831)	
Disaster(m)		-16.6728*		-0.0866***		-6.1917		-0.0639**
		(9.2861)		(0.0299)		(8.6971)		(0.0307)
Geographic proximity(m)		-441.6262		-3.2343***		-151.3764		3.4289
		(310.8092)		(0.8085)		(727.4870)		(3.3956)
Macro ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	No	No	No	No
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State×Year FE	No	No	No	No	Yes	Yes	Yes	Yes

Notes: 1) Results of regressions of county-level annual deposits on *Social Proximity to Disaster* (*Social proximity*) and controls. All independent variables are lagged one year relative to the dependent variable. 2) Macro controls in columns 1-2 and 5-6 are one-year lagged county GDP per capita and one-year lagged population, and macro controls in columns 3-4 and 7-8 are lagged percentage change in county GDP and lagged percentage change in population. 3) Data is from SHELDUS, FDIC Summary of Deposits, and BEA, during the time period January 2007-July 2019. All variables defined in Table A.1. All variables winsorized at the 1% level in both tails. 4) $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. Standard errors clustered at the county level.

Table 3: County-level deposits: excluding high net migration counties

	(1)	(2)	(3)	(4)
	Deposit amount ($1000s)		Deposit growth (p.p.)	
Social proximity(n) ex-high migration	299.5001***		2.7739***	
	(44.2314)		(0.3466)	
Social proximity(m) ex-high migration		714.1556***		8.2567***
		(101.4553)		(1.0454)
Observations	27,435	27,435	27,425	27,425
Adj R^2	0.9871	0.9871	0.0838	0.0835
Disaster+Geographic proximity	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes

Notes: 1) Results of regressions of county-level annual deposits on *Social proximity ex-high migration* and controls. *Social proximity ex-high migration* excludes connected counties for which net migration is above the 90th percentile. All independent variables are lagged one year relative to the dependent variable. 2) *Disaster* controls are the disaster measures for the focal county (i.e., disaster measures computed for county i), and *Geographic proximity* controls are geographic distance-weighted disaster exposures. Macro controls in columns 1-2 are one-year lagged county GDP per capita and one-year lagged population, and macro controls in columns 3-4 are lagged percentage change in county GDP and lagged percentage change in population. 3) Data is from SHELDUS, FDIC Summary of Deposits, the Census ACS, and the BEA, during the time period January 2011-July 2019. All variables defined in Table A.1. All variables winsorized at the 1% level in both tails. 4) $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. Standard errors clustered at the county level.

Table 4: County-level deposits: the importance of granular SCI value

	Social proximity (top 10)					*Unweighted social proximity* (top 10)			
	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
	Dep amount ($1000s)		Dep growth (p.p.)			Dep amount ($1000s)		Dep growth (p.p.)	
Social proximity(n)	251.2510***		1.5714***		Unweighted social proximity(n)	-8.3317**		0.0346**	
	(67.4101)		(0.3770)			(4.1873)		(0.0152)	
Social proximity(m)		794.3312***		5.9847***	Unweighted social proximity(m)		-25.5381**		0.1021*
		(146.1120)		(1.1022)			(11.5525)		(0.0562)
Observations	39,634	39,634	39,621	39,621		39,634	39,634	39,621	39,621
Adj R^2	0.9791	0.9791	0.0778	0.0781		0.9791	0.9791	0.0771	0.0779
Disaster+Geographic proximity	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Macro ctrls	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes

	Social proximity (rank only)			
	(1)	(2)	(3)	(4)
	Deposit amount ($1000s)		Deposit growth (p.p.)	
Social proximity(n) (rank only)	-1.0400		-0.0064	
	(3.0239)		(0.0098)	
Social proximity(m) (rank only)		-7.2400		0.0361
		(8.4693)		(0.0346)
Observations	39,634	39,634	39,621	39,621
Adj R^2	0.9790	0.9790	0.0771	0.0772
Disaster+Geographic proximity	Yes	Yes	Yes	Yes
Macro ctrls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes

Notes: 1) Results of regressions of county-level annual deposits on disaster measures and controls. All independent variables are lagged one year relative to the dependent variable. In columns 1-4 of the top panel the main independent variables are the two *Social Proximity to Disaster* (*Social proximity*) measures computed based on the top ten connected counties only. In columns 5-8 of the top panel the main independent variables are the two *Unweighted Social Proximity to Disaster* (*Unweighted social proximity*) measures computed based on the top ten connected counties only. In the bottom panel the main independent variables are the two *Social Proximity to Disaster (rank only* (*Social proximity (rank only)*) measures computed for all connected counties. 2) *Disaster* controls are the disaster measures for the focal county (i.e., disaster measures computed for county i), and *Geographic proximity* controls are geographic distance-weighted disaster exposures. Macro controls in the deposit amount regressions are one-year lagged county GDP per capita and one-year lagged population, and macro controls in the deposit growth specifications are lagged percentage change in county GDP and lagged percentage change in population. 3) Data is from SHELDUS, FDIC Summary of Deposits, and BEA during the time period January 2007-July 2019. All variables defined in Table A.1. All variables winsorized at the 1% level in both tails. 4) $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. Standard errors clustered at the county level.

Table 5: County-level deposits: disaster frequency v.s. monetary impact

	(1)	(2)	(3)	(4)
	Deposit amount ($thousands)		Deposit growth (p.p.)	
Social proximity(n)	104.8865***		0.7420**	
	(39.2515)		(0.3313)	
Social proximity(m)		440.9794***		2.4042**
		(107.2800)		(1.1515)
Social proximity (dollar damage)	834.6425***	470.9784***	16.0566***	14.0701***
	(143.6413)	(124.6329)	(2.6350)	(3.1603)
Observations	39,634	39,634	39,621	39,621
Adj R^2	0.9791	0.9791	0.0799	0.0804
Disaster+Geographic proximity	Yes	Yes	Yes	Yes
Macro ctrls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes

Notes: 1) Results of regressions of county-level annual deposits on *Social Proximity to Disaster* (*Social proximity*) and controls. All independent variables are lagged one year relative to the dependent variable. *Social proximity (dollar damage)* is equal to 1 if the total dollar damage is in the 75th percentile, and 0 otherwise. 2) *Disaster* controls are the disaster measures for the focal county (i.e., disaster measures computed for county i), and *Geographic proximity* controls are geographic distance-weighted disaster exposures. Macro controls in columns 1-2 are one-year lagged county GDP per capita and one-year lagged population, and macro controls in columns 3-4 are lagged percentage change in county GDP and lagged percentage change in population. 3) Data is from SHELDUS, FDIC Summary of Deposits, and BEA, during the time period January 2007-July 2019. All variables defined in Table A.1. All variables winsorized at the 1% level in both tails. 4) $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. Standard errors clustered at the county level.

Table 6: County-level deposits: excluding counties that share banks

	(1)	(2)	(3)	(4)
	Deposit amount ($thousands)		Deposit growth (p.p.)	
Social proximity - no bank overlap(n)	346.3137***		4.7803***	
	(52.0559)		(0.5193)	
Social proximity - no bank overlap(m)		1,058.5862***		14.1546***
		(140.0512)		(1.3858)
Observations	39,622	39,622	39,621	39,621
Adj R^2	0.9791	0.9791	0.0802	0.0807
Disaster+Geographic proximity	Yes	Yes	Yes	Yes
Macro ctrls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes

Notes: 1) Results of regressions of county-level annual deposits on *Social Proximity to Disaster - no bank overlap* (*Social proximity - no bank overlap*) and controls. County pairs that share at least one bank are *excluded* from the calculation of *Social proximity - no bank overlap*. All independent variables are lagged one year relative to the dependent variable. 2) *Disaster* controls are the disaster measures for the focal county (i.e., disaster measures computed for county i), and *Geographic proximity* controls are geographic distance-weighted disaster exposures. Macro controls in columns 1-2 are one-year lagged county GDP per capita and one-year lagged population, and macro controls in columns 3-4 are lagged percentage change in county GDP and lagged percentage change in population. 3) Data is from SHELDUS, FDIC Summary of Deposits, and BEA, during the time period January 2007-July 2019. All variables defined in Table A.1. All variables winsorized at the 1% level in both tails. 4) $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. Standard errors clustered at the county level.

Table 7: County-level deposits: controlling for migration inflows from disaster-impacted counties

	(1)	(2)	(3)	(4)
	Deposit amount ($thousands)		Deposit growth (p.p.)	
Social proximity(n)	294.8975***		0.6122	
	(44.7790)		(0.5044)	
Social proximity(m)		662.5032***		3.9357***
		(104.1495)		(1.5168)
Disaster-weighted migration	-2,013.8824	-2,179.8877		
	(1,417.5426)	(1,446.5729)		
Disaster-weighted migration change			-0.0497*	-0.0492*
			(0.0292)	(0.0291)
Net migration	378.1242	309.5805		
	(358.7506)	(359.5101)		
Net migration change			0.0036	0.0036
			(0.0040)	(0.0041)
Observations	22,317	22,317	18,504	18,504
Adj R^2	0.9897	0.9897	0.0876	0.0866
Disaster+Geographic proximity	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes

Notes: 1) Results of regressions of county-level annual deposits on *Social Proximity to Disaster* (*Social proximity*) and controls. The variable $Disaster - weighted\ migration$ is disaster-weighted migration into county i in year t, and the variable *Net migration* is equal to average net migration in county i in year t. All independent variables are lagged one year relative to the dependent variable. 2) *Disaster* controls are the disaster measures for the focal county (i.e., disaster measures computed for county i), and *Geographic proximity* controls are geographic distance-weighted disaster exposures. Macro controls in columns 1-2 are one-year lagged county GDP per capita and one-year lagged population, and macro controls in columns 3-4 are lagged percentage change in county GDP and lagged percentage change in population. 3) Data is from SHELDUS, FDIC Summary of Deposits, the Census ACS, and the BEA, during the time period January 2011-July 2019. All variables defined in Table A.1. All variables winsorized at the 1% level in both tails. 4) $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. Standard errors clustered at the county level.

Table 8: County-level deposits: controlling for economic similarity

	(1)	(2)	(3)	(4)
	Deposit amount ($thousands)		Deposit growth (p.p.)	
Social proximity(n)	171.2278***		1.9659***	
	(38.0118)		(0.2845)	
Economic proximity(n)	0.0155		0.0000	
	(0.0100)		(0.0000)	
Social proximity(m)		573.4552***		6.3700***
		(97.4379)		(0.8409)
Economic proximity(m)		-0.0163		-0.0005***
		(0.0489)		(0.0002)
Observations	39,634	39,634	39,621	39,621
Adjusted R^2	0.9791	0.9791	0.0785	0.0799
Disaster+Geographic proximity	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes

Notes: 1) Results of regressions of county-level annual deposits on *Social Proximity to Disaster* (*Social proximity*) and controls. The variable *Economic proximity* is disaster-weighted industry cosine similarity for county i in year t. All independent variables are lagged one year relative to the dependent variable. 2) *Disaster* controls are the disaster measures for the focal county (i.e., disaster measures computed for county i), and *Geographic proximity* controls are geographic distance-weighted disaster exposures. Macro controls in columns 1-2 are one-year lagged county GDP per capita and one-year lagged population, and macro controls in columns 3-4 are lagged percentage change in county GDP and lagged percentage change in population. 3) Data is from SHELDUS, FDIC Summary of Deposits, the Census ACS, and the BEA, during the time period January 2007-July 2019. All variables defined in Table A.1. All variables winsorized at the 1% level in both tails. 4) $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. Standard errors clustered at the county level.

Table 9: County-level deposits: excluding geographically close counties

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Remove Top 10				Remove Top 20			
	Amount ($1000s)		Growth (p.p.)		Amount ($1000s)		Growth (p.p.)	
Social proximity(n)	742.5***		9.522***		1,161***		14.41***	
	(124.3)		(0.940)		(186.2)		(1.353)	
Social proximity(m)		2,764***		31.71***		4,491***		48.48***
		(374.4)		(2.726)		(576.4)		(4.136)
Observations	39,634	39,634	39,621	39,621	39,634	39,634	39,621	39,621
Adj R^2	0.981	0.981	0.151	0.153	0.981	0.981	0.152	0.153

	Remove Top 50				Remove Top 100			
	Amount ($1000s)		Growth (p.p.)		Amount ($1000s)		Growth (p.p.)	
Social proximity(n)	2,360***		23.01***		4,409***		33.58***	
	(353.0)		(2.147)		(664.7)		(3.721)	
Social proximity(m)		9,697***		84.61***		20,191***		143.9***
		(1,185)		(7.193)		(2,446)		(12.34)
Observations	39,634	39,634	39,621	39,621	39,634	39,634	39,621	39,621
Adj R^2	0.981	0.981	0.151	0.153	0.981	0.981	0.151	0.153
Disaster+Geographic proximity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: 1) Results of regressions of county-level annual deposits on *Social Proximity to Disaster* (*Social proximity*) and controls. In the top panel, columns 1-4 (5-8) remove the top 10 (top 20) closest counties by physical distance. In the bottom panel, columns 1-4 (5-8) remove the top 50 (top 100) closest counties by physical distance. All independent variables are lagged one year relative to the dependent variable. 2) *Disaster* controls are the disaster measures for the focal county (i.e., disaster measures computed for county i), and *Geographic proximity* controls are geographic distance-weighted disaster exposures. Macro controls in columns 1-4 are one-year lagged county GDP per capita and one-year lagged population, and macro controls in columns 5-8 are lagged percentage change in county GDP and lagged percentage change in population. 3) Data is from SHELDUS, FDIC Summary of Deposits, and BEA, during the time period January 2007-July 2019. All variables defined in Table A.1. All variables winsorized at the 1% level in both tails. 4) $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. Standard errors clustered at the county level.

Table 10: Bank-level deposits

	(1)	(2)	(3)	(4)
	Amount ($thousands)		Growth (p.p.)	
Bank social proximity(n)	145.3770***		0.0116***	
	(19.4875)		(0.0030)	
Bank social proximity(m)		430.0535***		0.0381***
		(63.7481)		(0.0089)
Observations	336,488	336,488	327,583	327,583
Adjusted R^2	0.9106	0.9106	0.0870	0.0865
Disaster+Geographic proximity	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes

Notes: 1) Results of regressions of bank-level quarterly deposits (columns 1-2) and deposit growth (columns 3-4) on *Bank Social Proximity to Disaster* (*Bank social proximity*) and controls. All independent variables are lagged one year relative to the dependent variable. 2) *Disaster* controls are the bank-level disaster measures for bank b (i.e., the weighted average disaster measures for all counties in which the bank takes deposits), and *Geographic proximity* controls are bank-level geographic distance-weighted disaster exposures. Bank controls are either levels of (columns 1-2) or changes in (columns 3-4) the following variables: log(assets), equity ratio, and income ratio. 3) Data is from SHELDUS and Call Reports during the time period January 2007-July 2019. All variables defined in Table A.1. All variables winsorized at the 1% level in both tails. 4) $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. Standard errors clustered at the bank level.

Table 11: Depositor social connectedness and bank deposit stability

	(1)	(2)	(3)	(4)	(5)	(6)
	Bank deposit volatility					
Bank SCI	-0.0001			0.0002		
	(0.0005)			(0.0005)		
I(>75 pctile Bank SCI)		6.0124			22.9103***	
		(6.4450)			(7.4772)	
I(>90 pctile Bank SCI)			22.9460***			39.3987***
			(6.4826)			(10.6309)
GeoDiv $\times Bank\,SCI$				-0.0009***		
				(0.0002)		
GeoDiv $\times I(>75th)$					-22.6177***	
					(6.8627)	
GeoDiv $\times I(>90th)$						-26.8783***
						(9.8395)
GeoDiv				-34.9398***	-43.3038***	-45.4506***
				(8.2733)	(7.3233)	(7.0437)
Observations	61,400	61,400	61,400	61,400	61,400	61,400
Adj R^2	0.8513	0.8513	0.8513	0.8521	0.8521	0.8521
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: 1) Results of regressions of bank-level annual deposit level volatility on bank SCI and controls. The variable *GeoDiv* is equal to 1 when a bank takes deposits in at least two counties in a given year, and 0 otherwise. The variables *I(>75 pctile Bank SCI)* and *I(>90 pctile Bank SCI)* are indicators equal to 1 when *Bank SCI* is above the 75th or 90th percentile, respectively, and 0 otherwise. Bank controls are log(assets), equity ratio, income ratio, and bank HHI. 2) Data is from Call Reports during the time period January 2007-July 2019. All variables defined in Table A.1. All variables winsorized at the 1% level in both tails. 3) $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. Standard errors clustered at the bank level.

A Appendix

Table A.1: Variable definitions

Variable	Definition
Disaster(n)	Total number of natural disasters
Disaster(m)	Total number of months during which disasters cause damage in the top 10 percentile, 0 otherwise
SCI	Social connectedness index as measured in Bailey et al. (2018b)
Social Proximity to Disaster	SCI-weighted disaster measure
Geographic Proximity to Disaster	Geographic distance-weighted disaster measure
Social proximity ex-high migration	SCI-weighted disaster measure in which high net migration county pairs are excluded
Unweighted Social Proximity to Disaster	Social Proximity to Disaster based on average of disaster measures for top ten connected counties
Social proximity (rank only)	Social Proximity to Disaster based on the rank of SCI
Social proximity (dollar damage)	SCI-weighted measure of disasters that result in dollar damage in the 75th percentile or above
Social proximity-no bank overlap	SCI-weighted disaster measure in which disaster measures for county pairs with branches of the same bank are set to 0
Disaster-weighted Migration	Disaster-weighted migration inflow into a county in a given year
Net Migration	Average net migration in a county-year
Economic Proximity to Disaster	Disaster-weighted industry cosine similarity for a county-year
County deposit amount	Dollar amount of deposits in county
County deposit growth	Percentage change in county level deposits
Bank deposit amount	Dollar amount of bank deposits
Bank deposit growth	Percentage change in the amount of bank deposits
GDP per capita	County GDP per capita
Population	County population
GDP growth	Percentage change in total county GDP
Population growth	Percentage change in county population
Bank size	Log of total bank assets
Equity ratio	Bank equity divided by assets
Income ratio	Bank equity divided by lagged assets
Bank Indirect Disaster Exposure (BIDE)	Bank-weighted CIDE
Bank SCI	The deposit-ratio weighted average SCI of all counties in which a bank collects deposits
Bank deposit vol	The rolling five-year standard deviation of bank deposit amount
Bank HHI	The deposit ratio weighted average of the branch deposit Herfindahl-Hirschman Index
GHHI	The geographic deposit Herfindahl-Hirschman Index
NonzeroGD	Indicator equal to 1 when a bank takes deposits in multiple counties in a given year, and 0 otherwise
I(>75 pctile Bank SCI)	Indicator equal to 1 when a bank-year is above the 75th percentile for BankSCI, and 0 otherwise
I(>90 pctile Bank SCI)	Indicator equal to 1 when a bank-year is above the 90th percentile for BankSCI, and 0 otherwise
Disprone	Indicator equal to 1 when a county experienced a number of disasters in the 75th percentile or above prior to the sample period

A.1 Historical disaster experience

The response of deposits to the indirect disaster exposure via social connections may be sensitive to counties' historical experience. If a county is located in an area where disasters commonly occur, then households in that county may respond differently compared to those in counties that experience few disasters. This is because disasters are likely to be more salient and tangible for households located in disaster-prone counties. In this section, we therefore examine whether our main results are driven by counties that have experienced many natural disasters in the past. To do so, we compute the number of total disasters each county i has experienced up until the start of our sample period. We label a county as "disaster prone" if the number of disasters experienced prior to our sample beginning is in the 75th percentile and above. We then define an indicator variable *Disprone* equal to 1 when a county is disaster prone and 0 otherwise, and interact it with *Social Proximity to Disaster*. The interaction term directly identifies whether being more disaster prone affects the response of deposits to changes in the indirect disaster exposure via social connections.

We present the results in Table A.2. The coefficients on *Social Proximity to Disaster* remain positive and significant for the level of, and growth in, deposits. The interaction terms *Social proximity* $\times$ *Disprone* are negative and significant for the level of deposits, but insignificant for deposit growth. This suggests that disaster prone counties actually experience incrementally lower deposits relative to less disaster prone counties, which would be consistent with households in disaster prone areas being more used to disasters based on their own experience. Overall, because the impact of *Social Proximity to Disaster* remains significant, we conclude that our results are not driven by disaster-prone counties.

Table A.2: Robustness: Disaster prone focal counties

	(1)	(2)	(3)	(4)
	Deposit amount (\$1000s)		Deposit growth (%)	
Social proximity(n)	183.6427***		1.9146***	
	(36.2363)		(0.3218)	
Social proximity(m)		625.6675***		6.6185***
		(96.3744)		(0.9122)
Social proximity(n) × Disprone	-73.0022**		0.2438	
	(34.9140)		(0.4399)	
Social proximity(m) × Disprone		-336.7410***		-1.2049
		(109.0197)		(1.5047)
Observations	39,634	39,634	39,621	39,621
Adj R^2	0.9791	0.9791	0.0785	0.0797
Disaster+Geographic proximity	Yes	Yes	Yes	Yes
Macro ctrls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes

Notes: 1) Results of regressions of county-level annual deposits on *Social Proximity to Disaster* (*Social proximity*) and controls. *Disprone* is equal to 1 when county i experienced a number of disasters prior to our sample in the 75th percentile and above, and 0 otherwise. All independent variables are lagged one year relative to the dependent variable. 2) *Disaster* controls are the disaster measures for the focal county (i.e., disaster measures computed for county i), and *Geographic proximity* controls are geographic distance-weighted disaster exposures. Macro controls in columns 1-2 are one-year lagged county GDP per capita and one-year lagged population, and macro controls in columns 3-4 are lagged percentage change in county GDP and lagged percentage change in population. 3) Data is from SHELDUS, FDIC Summary of Deposits, and BEA, during the time period January 2007-July 2019. All variables defined in Table A.1. All variables winsorized at the 1% level in both tails. 4) $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. Standard errors clustered at the county level.