Direct and Indirect Impacts of Natural Disasters on Banks:

A Spatial Framework[1]

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In Memoriam

To

James R. Barth

(1943-2023)

He was a friend, mentor, and beloved colleague to all of those whose lives he touched

Direct and Indirect Impacts of Natural Disasters on Banks: A Spatial Framework

Abstract

We examine the direct and indirect impacts of natural disasters on deposit rates of U.S. bank branches from 2008 to 2017. We capture the indirect impact by the spatial spillover effects of disasters, from branches directly exposed to such disasters to neighboring branches. We theoretically motivate our spatial framework by local competition for deposits among branches and provide empirical evidence consistent with this model. We find that indirect effects contribute to at least two-thirds of the total impact for deposit rate-setting branches. Rate-setting branches in affected counties, on average, raise their deposit rates on 12-month CDs by 1.5 basis points directly due to the disaster shock. However, there is an additional indirect increase of 2.7 – 4.3 basis points for all rate-setting branches, including those in adjacent but unaffected counties, due to the local geographical competition for deposits. We also confirm that the spillover effect occurs among branches across counties via an overlooked social connectedness. Moreover, and importantly, online and one-county banks are more likely to rely on the information channel embedded in the social connectedness effect in response to natural disasters. Branches in less concentrated local markets also respond more to nature disasters and rate adjustments of neighboring branches.

JEL Codes: G21; C31; Q54

Keywords: Banks; Bank branches; Deposit rates; Natural disasters; Spatial analysis

1. Introduction

Our study analyzes the spillover effects of natural disasters on bank branches' deposit rates via local geographic and information channels. Natural disasters, including hurricanes, tornados, floods, wildfires, and earthquakes, can cause a loss of life and severe property damage to homes, offices, stores, and automobiles.[2] Boustan et al. (2020) point out that this is not a rare or recent problem since about 500 natural disasters have occurred throughout the United States each year during the past century. Moreover, the number of disasters has roughly tripled to 1,500 since the turn of the century. Furthermore, according to Deryugina (2017), the damage caused by natural disasters has grown faster than GDP over time.

Funds available to individuals and businesses to repair the damage caused by natural disasters come from private insurance policies and disaster relief from state and federal agencies. However, these funds are typically insufficient to cover the total amount needed to repair the damage (Federal Reserve Banks of Dallas, New York, Richmond and Francisco, 2018). An additional and essential source of funds is from banks and their branches located in counties throughout the country. Individuals and business owners suffering damages can withdraw deposits and apply for loans at local branches to obtain supplemental funding for reconstruction efforts. Banks can therefore play a critical and supporting role as deposits can be withdrawn and additional credit extended in response to such adverse shocks to local communities. Indeed, even the Federal Deposit Insurance Corporation (FDIC, 2018) recognizes banks' vital role in response to various natural disasters by encouraging banks in the affected areas to meet their communities' resulting financial services needs.

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[2] The exogeneity of some natural disasters may be subject to dispute over longer periods of time. Some may argue that human actions can contribute to future disasters due to their effect on, for example, deforestation and global warming. However, in the short run, this is unlikely to be the case for the types of natural disasters considered here.

Both theoretical and empirical studies have examined the impact of natural disasters on financial institutions. In one of the earliest studies of the effect of natural disasters on financial institutions, Steindl and Weinrobe (1983) argue that banks experience an increase in deposits in the immediate post-disaster period. In contrast, Brei et al. (2019) find that banks experience a negative funding shock in the form of deposit withdrawals following hurricanes in the Eastern Caribbean. According to them, the response of banks is to reduce their lending. However, Cortes and Strahan (2017) find that bank lending, in the form of home mortgage originations, increases significantly during the months following disasters as residents in the affected communities rebuild destroyed or damaged physical structures and banks, therefore, shift credit from other unaffected areas. Ivanov et al. (2022) find a similar result using syndicated lending for midsized and large companies. Small firms tend to drawdown their credit lines, with banks charging higher interest rates and offering less borrower-friendly loan terms (Brown et al., 2021). Furthermore, Bos et al. (2022) examine the causal effect of natural disasters on bank asset allocations and find that total loans, in general, and real estate loans, in particular, significantly increase after natural disasters. In a different focus, Schüwer et al. (2019) argue that affected banks may face significant loan quality issues caused by business failures, the loss of jobs, and uninsured or underinsured collateral damages. In response, according to them, banks, especially independent banks, increase their risk-based capital ratios after disasters.

However, until recent years there have been relatively limited studies examining the disaster impacts on bank deposit rates. Banks can raise deposit rates to obtain additional funding to meet unexpected high deposit withdrawals and loan demand in counties adversely affected by natural disasters. Among these studies, Cortes and Strahan (2017) find that branches exposed to natural disasters raise deposit rates to fund increased loan demand. Also, Dlugosz et al. (2022)

examine the deposit response of branches following natural disasters. They focus on whether branches of banks in affected communities can set deposit rates locally to attract additional deposits to meet the increase in loan demand for the reconstruction that takes place. Using a triple difference-in-differences (hereafter, DID) approach, they find that branches that set rates locally do increase deposit rates more in counties affected by natural disasters.

In contrast to these important studies, we address the spillover effects of natural disasters by measuring and controlling for the local geographic and information channels through which spillovers impact branches' deposit rates. Specifically, we use a spatial DID framework to decompose the impact of disasters on changes in branch deposit rates into direct and indirect effects, which have been largely overlooked in the existing literature. The direct effect captures how a branch located in the affected county[3] responds by changing its deposit rate to a disaster, without considering the competitive effect of the change on other branches in the local market. By comparison, such an indirect effect measures the response of all branches (located in the affected and unaffected adjacent counties) in the local market to the disaster via strategic interactions.[4] Our research design extends and thereby contributes to existing studies by providing causal evidence on the intra- and inter-geographical effects of natural disasters in three aspects. First, we capture overlooked spatial spillover effects of natural disasters on the deposit rate of branches in unaffected counties, based on their geographic distance from branches in affected counties. Accounting for these two effects identifies the total deposit rate response of branches to natural disasters. Second,

[3] A county is a commonly used geographical market definition in studies of bank branches. See, for example, Drechsler et al. (2017) and Cortes and Strahan (2017).

[4] Note that our definition of "indirect effect" is more general than "spillover effects" in previous studies. The "spillover effects" in previous studies either captures the affected bank behaviors in unaffected adjacent areas (e.g., Rehbein and Ongena, 2022; Ivanov et al., 2022; Cortes and Strahan, 2017) or captures the impact of other banks in unaffected areas (e.g., Koetter et al., 2020). In contrast, our "indirect effect" captures the effect of disasters on all branches, including branches in affected and unaffected areas. We argue that those branches in affected areas may also undertake an "indirect effect" probably due to the local geographical competition. We use "indirect effect" and "spillover effects" in the main text interchangeably with this distinction in mind.

we adopt a novel dataset on social connectedness networks to capture the information channel linking branches in neighboring counties. Depositors in unaffected markets can respond when their families and friends suffer natural disasters. Importantly, our data allows us to identify heterogeneous responses to a natural disaster via the degree of social connectedness, and thus determine whether there is a difference between geographical and social connectedness spillover channels in deposit rate adjustments following natural disasters. Third, based on our empirical design, we can evaluate the extent to which spatial competition among banks affects the multimarket rate setting of their branches due to shocks in local deposit markets. This analysis is valuable in providing information on the decision-making delegation in the banking system.

We find that branches increase deposit rates after natural disasters. We also find that the spatial spillover effect, or indirect effect, has a far larger effect than the direct effect. Compared to rate-setters in unaffected adjacent counties, rate-setting branches in affected counties, on average, raise their deposit rates on 12-month CDs by 1.5 basis points directly due to the disaster shock, which aligns with findings from Dlugosz et al. (2022). Yet, deposit rates of all branches increase an additional 2.7 to 4.3 basis points indirectly, driven by strategic interactions among local branches. Moreover, we find that local competition plays an important role in driving the indirect effect. This indirect effect occurs among branches across counties via both social connectedness and geographical networks, with the latter channel dominating, and the indirect effect at the branch level increases when the local market becomes more competitive.

A recent literature survey by Furukawa et al. (2020) underscores our focus on spatial spillover effects by documenting how natural disasters can affect banks' credit supply even in areas not directly affected by disasters due to the geographical expansion of the branch network of banks. Importantly, our results are robust using alternative spatial weighting matrices, deposit products, and controlling for year-coastal-metropolitan fixed effects.

The spillover effects on the geographical and social networks motivate us to also investigate whether the spillover effects are more pronounced in certain banks. Therefore, we analyze online banks, which heavily invest in technology, and one-county banks, with all branches located in one county. This approach allows us to check whether such banks respond differently than other banks relying more heavily on branch networks and those more geographically dispersed to natural disasters. We find a greater response for more online-oriented banks to a disaster in the neighboring counties via the social network channel. We suspect the reason is that online banks provide better services through a mobile app or a website than their counterparts, which rely more on brick-and-mortar operations. We also find a stronger indirect effect for one-county banks, which depend more on and respond more to local market conditions than banks operating across multiple counties or nationwide. Branches in less concentrated local markets tend to respond more to the neighboring branches' adjustments and the disaster via the informational channel.

To summarize, our research design contributes to multiple strands of literature. First, we contribute to the literature on modeling and estimating spillover effects in finance and economics. Exogenous shocks to local market conditions can, in theory, result in aggregate fluctuations through the production network (Acemoglu et al., 2012) and induce systematic risks in the financial network (Acemoglu et al., 2015). Studying potential spillover effects helps to capture the general equilibrium impacts of exogenous shocks, rather than focusing on only the direct partial equilibrium outcomes. For instance, Huber (2018) finds that reduced lending by a large bank affects firms independent of their banking relationship through lower aggregate demand and geographical agglomeration spillover effects. Given such spillover effects, it is important to disentangle the direct and indirect impacts of the exogenous shocks. In this regard, we employ the spatial framework as the empirical strategy to allow for spillovers in branch-banking business decisions in response to local natural disasters. Natural disasters obviously impact local economies and can have both direct and indirect impacts since the banking networks are connected via geographical and social network channels. Our spatial approach allows one to decompose the total effects into direct and indirect impacts to identify the major source of impact. This decomposition, therefore, provides a more comprehensive understanding of how firms respond to local exogenous shocks, allowing policymakers to weigh the pros and cons of changes in their financial policies in a more informative manner.

Second, we make a methodological contribution by using a spatial DID framework and connecting it to the causal inference literature. Traditional DID frameworks face the challenge of dealing with a treatment externality, such as the existence of spillover effects, which violates the stable unit treatment value assumption (SUTVA). The spatial DID framework allows relaxing this assumption so that unit i's outcomes can depend on the treatment status of unit $j \neq i$. As emphasized by Berg et al. (2021), the existence of spillover effects naturally implies that SUTVA is violated. Even when the treatment is randomly assigned, spillovers lead to a bias in estimating treatment effects, and the inclusion of fixed effects does not necessarily alleviate the bias. The recent review on difference-in-differences (Roth et al., 2022) also mentions spillover effects as one of the future research directions appropriate in a DID framework. Our spatial DID framework addresses the spillover in both outcome and treatment and hence contributes to the growing literature on the econometrics of DID.

Third, our study also contributes to the literature studying the propagation of negative shocks in the banking industry. The negative impact of natural disasters on economic activities has been widely documented (e.g., Baker and Bloom, 2013; Cavallo et al., 2013; Boustan et al., 2020; Brown et al., 2021), but the related spillover effects have not been widely explored. Cortes and Strahan (2017), Ivanov et al. (2022), Rehbein and Ongena (2022) examine how bank lending networks propagate the shocks of natural disasters. They find that banks cut lending in unaffected markets to meet the increased loan demand in affected areas. Koetter et al. (2020) document that after natural disasters banks in unaffected counties also increase lending to firms inside affected counties. Unlike these papers that study bank loan allocation after natural disasters, we use a bank pricing strategy on deposit products to examine how local natural disaster shocks propagate through bank networks. Moreover, we also decompose the spillover effects to capture geographical competitive and social connectedness channels. To the best of our knowledge, only one paper studies the impact of social connectedness on bank funding. Flynn and Wang (2022) find that counties experience an increase in bank deposits when they are more socially connected to counties affected by natural disasters. But we differ from their paper by being the first to study the relationship between geographical competitive and social networks.

Finally, our paper contributes to empirical studies on competition effects in the retail banking industry. Competition in the banking industry is widely explored in the literature (e.g., Boyd and De Nicolo, 2005; Duqi et al., 2021; De Haas et al., 2021; Wang, 2021; Degryse et al., 2009; Degryse and Ongena, 2005). We believe our study provides a new perspective on competition at a local geographical level. Applying a spatial framework to study the spillover effects of natural disasters on bank branches is well suited for capturing the local competition effects among multimarket bank branches (Hannan and Prager, 2004). Our empirical method can also motivate applications in other industries where strategic competition exists (Dou et al., 2021).

Regarding policy implications, the significance of the local competition effect among branches highlights the crucial issue of insufficient exposure by individuals to adequate financial services in rural areas. In this regard, our study echoes a recent Federal Reserve report on the access to bank branches in rural communities from the perspective of local disasters. As the report states (Dumont and Roberts, 2019): "… between 2012 and 2017, more than 100 banking markets went from containing the headquarters of at least one bank to containing no bank's headquarters. Almost all of these markets with no bank headquarters are rural." The closure or exit of banks' headquarters in rural areas likely contributes to a decrease in the number of branches and thus rate-setters in such markets. According to our findings, such declines further reduce the financial resilience in these areas once natural disasters strike, as deposit rates become unresponsive to local increases in loan demand in the absence of rate-setter branches.

The remainder of the paper proceeds as follows. Section 2 presents a theoretical framework for the setting of deposit rates by bank branches as a motivation for our empirical analysis. Section 3 discusses the variables used in the empirical analysis and the data sources. Section 4 presents the empirical specifications for the estimated non-spatial and spatial models. Section 5 presents and discusses the empirical results. Section 6 focuses on the heterogeneity in the behavioral responses of different types of banks. Section 7 presents a series of robustness checks. Section 8 concludes.

2. Theoretical framework

The model we develop extends Barros (1999) and Hannan and Prager (2004) to incorporate pricing competition among bank deposit-rate setters operating in multiple local markets. Local competition could be one of the important channels that explain the spillover of deposit rates across neighboring branches, and we use the monopolistic competition to motivate our empirical spatial framework.[5] The rate-setters compete for deposits based on the rate set for deposits within the monopolistic competition framework of Salop (1979).

Assume a rate-setter branch s of bank b sets the deposit rates r_s, for all of bank b's n_s branches located in all K_s local markets, such as counties K_s. The total n_k branches in local market k belong to the group of banks B_k, while n_{ks} is the number of branches whose deposit rate is set by the rate-setter s in market k. In the spirit of Salop (1979), we assume that n_k branches are uniformly distributed in a unit circle and local depositors are uniformly located along the circle with density δ_k. We further assume each depositor saves one unit of deposits and incurs the unit travel cost t for the distance between the depositor and the nearest branch. Hence, the density δ_k proxies the total volume of deposits available in market k. Here an implicit assumption is that depositors in market k cannot choose branches in other markets. In other words, the branches in other markets are sufficiently far away from the depositors to prevent this option.[6]

Now, assuming anonymity of identity of two neighbor branches, there is a $(n_{ks} - 1)/(n_k - 1)$ probability that a neighboring branch belongs to the same bank. The expected deposits of branch i under the rate setter's influence given deposit rates of all branches in market k is:

$$E(D_{isk}) = \delta_k \left[\frac{1}{n_k} + \frac{1}{t} \left(\frac{n_k - n_{ks}}{n_k - 1} r_s - \sum_{j \in B_k \setminus b} \frac{n_{kj}}{n_k - 1} r_j \right) \right], \tag{1}$$

where r_s is the deposit rate set by branch s for all branches of bank b in market k, and r_j denotes deposit rates of branches from bank j in group B_k other than b. We also presume that branches

[5] Other channels like coordination, collusion and supply chains also can lead to spatial spillovers of deposit rates. For example, Oh (2012) uses a spatial autogression to study the collusion of local small banks. We appreciate the two anonymous referees for pointing this out. Our data do not allow us to identify the independent sources of spillovers and empirically test and differentiate the different channels, and we leave such further analyses of the relative strength of alternative mechanisms to future work.

[6] Each depositor has its own definition of the "local market" in mind and adjacent markets can overlap. We feel that this simplifying assumption has currency given the distances we are using in defining such a local market and allows us to focus on the rate decision.

from the same bank in the same county follow the deposit rate mandated by a rate-setter branch.

The profit π due to the rate-setter branch s is determined by the total deposits of all affiliate branches n_s in K_s markets, and thus it can be expressed as

$$\pi_s = (\bar{r} - r_s) \times \sum_{k \in K_s} n_{ks} E(D_{isk}) \ , \tag{2}$$

where $\bar{r}$ is the rate of return on assets acquired with the deposits and assumed exogenous to the deposit rate r_s.[7] Profit maximization implies the first-order condition of $\partial \pi_s / \partial r_s = 0$, which leads to the following optimal deposit rate:

$$r_s^* = \frac{1}{2}\bar{r} - \frac{t \sum_{k \in K_s} \delta_k n_{ks} / n_k}{2 \sum_{k \in K_s} \delta_k n_{ks} l_{ks}} + \frac{\sum_{k \in K_s} (\delta_k n_{ks} \sum_{j \in B_k \setminus b} \left(\frac{n_{kj}}{n_k - 1} \right) r_j)}{2 \sum_{k \in K_s} \delta_k n_{ks} l_{ks}}, \tag{3}$$

where $l_{ks} \equiv (n_k - n_{ks})/(n_k - 1)$. This expression can be further simplified as

$$r_s^* = \frac{1}{2}\bar{r} - \frac{t}{2} \sum_{k \in K_s} \frac{\omega_{ks}}{n_k} + \frac{1}{2} \sum_{k \in K_s} \sum_{j \in B_k \setminus b} \frac{n_{kj}}{n_k - 1} \omega_{ks} r_j, \tag{4}$$

where $\omega_{ks} \equiv \delta_k n_{ks} / \sum_{k \in K_s} \delta_k n_{ks} l_{ks}$, which measures the relative importance of market k for the rate setter s in terms of local depositors' density and the number of branches. Since we assume no entry and exit of branches during the disaster period, n_{ks} and l_{ks} are fixed. Therefore, ω_{ks} is driven by the change of the density δ_k in our setting.

The competition effect implies that the setter branch s will raise its deposit rate when a rival bank branch increases its rate, namely r_j, as shown in the last term in equation (4). Rate-setter branches can adjust their rates in response to both natural disasters and rate changes by competitor bank branches.

[7] Since the focus is on the deposit rate in a spatial setting, we abstract from the endogeneity of $\bar{r}$, such as the change of the loan rate due to a local disaster. We leave the potential interaction between deposit and loan rates in a branch rate setting for future research.

To motivate the spatial autoregression based on the model, let first $\Delta r_s = r_s^{\text{post}} - r_s^{\text{pre}}$ denote the deposit rate change after the disaster, and correspondingly the change of relative importance of local market *k* for the rate setter *s*: $\Delta\omega_{ks} = \omega_{ks}^{post} - \omega_{ks}^{pre}$.[8] Therefore, equation (4) is modified for the resulting change in the deposit rate as follows:

$$\Delta r_s = \underbrace{-\frac{t}{2}\sum_{k\in K_s}\frac{1}{n_k}\Delta\omega_{ks}}_{Direct\ effect} + \underbrace{\frac{1}{2}\sum_{k\in K_s}\sum_{j\in B_k\setminus b}\frac{n_{kj}}{n_k-1}\left(\omega_{ks}^{\text{post}}\Delta r_j + \Delta\omega_{ks} r_j^{\text{post}}\right)}_{Indirect\ effect}. \tag{5}$$

When a local disaster strikes market k, the negative exogenous shock that lowers the local depositors' density δ_k can be attributed to various factors. In order to finance the reconstruction of damaged properties, households or local business owners may withdraw a larger portion of their deposits or seek increased borrowing options such as credit cards, lines of credit, or loans from their respective banks. Also, disruptions in the supply chain caused by the shock may necessitate extra funding for downstream firms. These firms may require additional financial support to maintain their operations and cope with the impact of the shock (Altay and Ramirez, 2010). Individuals and businesses in neighboring regions may increase deposit withdrawals due to an increase in housing prices (Allen et al., 2022) and lower earnings (Belasen and Polachek, 2009).[9]

Since $\partial\omega/\partial\delta > 0$, a smaller deposit density δ_k leads to a decrease in ω_{ks}, and the rate setter *s* would respond to the drop in deposits in market *k* by raising its deposit rate to prevent a decline in funding for loans. As a result, the first term in equation (5) is positive, which incentivizes the branch setter to increase the deposit rate absent any strategic interaction with other banks. This motivates the first hypothesis on the direct impacts of disasters:

[8] Here, we suppress the symbol * denoting the optimal solution.

[9] We appreciate the suggestion from the anonymous referee to provide clearer interpretations regarding δ_k. Among the three reasons we presented, the first reason indicates a direct impact, whereas the latter two reasons contribute to indirect spillover effects on changes in bank deposit rates.

Hypothesis 1: the direct effect of disasters on the rate setter's deposit rate is positive.

Despite the data not informing us of the specific travel cost and deposit density, we can test the sign of the coefficient for the setter's rate change when a disaster strikes its branch in the county in which it is located in our empirical model. We expect a positive sign for the direct effect[10].

The first term in equation (5) is only the direct effect since it does not account for spillover effects on deposit rates of other banks' branches in other counties. When one includes the second term in equation (5), which is the indirect effect that captures competition among neighboring branches of other banks, the sign of the total effect of a natural disaster on the change in the deposit rate becomes ambiguous. Two opposing channels contribute to the indirect effect due to the change of rival banks' deposit rates: (i) an increase in rivals' rates causes rate-setters to raise their deposit rates via market competition and other spillover effects as δ_k decreases; vs. (ii) a decrease in the relative importance of market k ($\Delta\omega_{ks} < 0$) that moderates the response of rate-setters that determine the uniform deposit rate across multiple markets. Our empirical spatial analysis focuses on the first channel to quantify the competition effect. Even if a rate setter determines there is no rate-taking branch in the affected county (that is $\Delta\omega_{\mathrm{ks}} \equiv 0, \forall\, k$), the pure competition effect may still drive up its deposit rate after the disaster as long as some local competitors are affected. Therefore, we propose a second hypothesis on the indirect competition effect:

Hypothesis 2: the indirect effect of disasters on branches' deposit rates via local market competition is positive.

The spatial specification in the empirical model enables us to explicitly capture how changes in deposit rates of nearby branches affect the rate setter's response when a disaster hits

[10] We do not incorporate the delegation of rate setting into our main empirical model for simplicity, but later discuss the implication for further robustness checks in Section 7.

the county in which it is located. We expect changes in deposit rates across branches in the affected and neighboring counties to be positively correlated, which would provide evidence consistent with the local competition effect among branches.

3. Data

3.1. Variables and data sources

The data for our study combines several datasets covering the period from October 2008 to December 2017. These datasets include information on natural disasters, deposit rates for each bank branch, bank balance-sheet variables, branch location, and social connectedness. We now describe in more detail the data used in the empirical work.

3.1.1. Natural disasters and damages

Data on natural disasters comes from two sources. Official declarations come from the Federal Emergency Management Agency (FEMA) database and property damage information from the Spatial Hazard Events and Losses Databases for the United States (SHELDUS). FEMA provides the declaration date of the disaster, location (county and state), and type of disaster. We include the following types of disasters in the analysis: fires, floods, hurricanes, snow, severe storms, tornados, and other disasters (see Figure A.1). Sampled branches are in the affected counties and their neighboring counties for every disaster. SHELDUS provides similar information. These two datasets allow us to identify affected/unaffected neighbor counties.[11] Different from Dlugosz et al. (2022), we discard human behavior-related disasters, including terrorist, chemical, and toxic substances, and instead focus only on natural disasters. Furthermore, unlike Dlugosz et al. (2022), whose sample period is 1999 – 2014, our analysis is more recent and

[11] The two datasets do not follow the same dating rule. Thus, we can only successfully match about one third of the total sample of natural disasters.

focuses on disasters from October 2008 to December 2017. The reason is that we want to avoid the potential confoundedness of the earlier and severe financial crisis.

Figure 1 shows the geographical distribution of the disaster damages at the county level. The figure shows that the most severe disasters occurred in the country's coastal areas. For illustration, the darker color represents more severe damage.

[Figure 1 About Here]

3.1.2. Branch deposit rates

We obtain deposit rate data from RateWatch, a firm that provides weekly branch-level data for such rates. Information is available for the location of branches (county and state), unique branch IDs assigned by the FDIC, and type of deposit products. RateWatch also identifies branches that establish their own rates, which we label as our rate-setter branches, as well as the corresponding branches that adopt these rates, which we classify as our rate-taker branches. The main outcome variable is the change of the pre-post deposit rate, measured by the 12-month CD rate, for each branch in the affected county and neighboring counties. Therefore, each branch has only two time periods (pre and post). We calculate the pre-post deposit rate change following Dlugosz et al. (2022), which includes a seven-month window with three months before and three months after the month of the disaster. The pre-rate is the average of the three months before the disaster, while the post-rate is the average of the three months following the disaster.

3.1.3. Branch deposits

Deposit data at the branch level are available from the FDIC's Summary of Deposits (SOD). SOD provides an annual survey of branch deposits as of June 30. The data also includes geographic information (county and state) of branches and bank headquarters and unique branch IDs assigned by the FDIC.

3.1.4. Explanatory variables

The data for the explanatory variables come from the quarterly Call Reports and the Statistics on Depository Institutions (SDI), FRED Economic Data, the American Community Survey (ACS), and Facebook (Bailey et al., 2018).

The bank variables include total assets, total deposits, total equity capital[12], total loans and leases, an MSA indicator, deposits/assets, equity capital ratio[13], a small bank indicator for a bank with less than $2 billion in assets. We follow Dlugosz et al. (2022) by including an indicator for a local market that takes the value of 1 when a bank receives more than 65 percent of its deposits from the county in which it is located to capture the relationship between bank and county. We also include an indicator for an important market that takes the value of 1 when a county ranks at the top quartile of deposits among all counties where the bank has branches.

The county-level demographic variables include the log of the total population, log of county median household income, percent white population, percent black population, and percent of the population with at least a college degree.[14] We also include monthly effective Federal Funds rates from Federal Reserve Economic Data to control for the change in the policy rate before and after a disaster.

In addition to the geographical network for branches, we use the Facebook Social Connectedness Index to measure the degree of social connectedness across counties. The current Social Connectedness Index provides a relative number of Facebook friendship links between

[12] Rehbein and Ongena (2022) find that low bank capital carries a negative externality because it amplifies local shock spillovers.

[13] Ivanov et al. (2022) find that banks meet an increase in credit due to natural disasters in part by reducing credit to communities unaffected by disasters. Banks with lower capital-to-asset ratios do this to a greater extent to lower the total credit risk exposure.

[14] A bank delegates the decision as to deposit rates to rate-setting branches. Since some characteristics might interact with how banks respond to natural disasters, various control variables are included, as discussed in Dlugosz et al. (2022). Moreover, the county characteristics included help control for heterogeneity across counties, as well as being informative about potential welfare effects.

individuals in two counties as of April 2016. The dataset was created by Bailey et al. (2018), and it quantifies the strength of social connectedness between U.S.-county pairs based on the number of friendship links on Facebook.[15]

Lastly, as discussed earlier regarding our model, a bank delegates authority to some branches to set deposit rates, or rate-setter branches, while its other branches become followers regarding those rates, or rate-taker branches. For example, in June 2017, Bank of America had 4,646 branches located in 35 states and 461 counties. Only 30 branches (in 30 different states and 30 counties) set the 12-month CD rate, while others were rate-takers. Similarly, Wells Fargo had 6,090 branches in 42 states and 929 counties. Only 49 branches (in 39 states and 49 counties) were rate-setters for the 12-month CD.[16] The delegation of rate-setting behavior to specific branches allows a bank to respond to local liquidity shocks by changing deposit rates in only those selected geographical areas affected. Banks, therefore, do not have to shift deposits from branches not affected to those that are, which may be more costly and disruptive to existing operations throughout their branch network. Thus, we include a variable to distinguish between rate-setters and rate-takers because the former drives the change in deposit rates due to a shock. Specifically, since we employ a difference-in-differences technique, the following dummy variables are included: an indicator of treatment/control branches (in affected/unaffected neighbor counties), deposit rate-setter branch (0-taker, 1-setter), and interaction of rate-setter branch with the treatment dummy.

3.2. Dataset construction

[15] Despite the fact that such connectedness may vary across time, we believe the current version well approximates the latent degree of social connectedness during our sample period from October 2008 to December 2017. There is a growing literature in finance using this dataset, for example, Kuchler and Stroebel (2021), Kuchler et al. (2022), Bailey et al. (2020), and Bailey et al. (2022).

[16] In our sample, as Table 1 shows, 10% of the branches are rate-setters.

To construct the dataset for our empirical estimation, we define the treated branches as those located in counties that experienced at least one disaster designated by FEMA during the sample period. We follow Dlugosz et al. (2022) to define "pre-disaster" as three months before the date of the disaster and "post-disaster" as three months after the declaration of the disaster. We then define control groups as branches located in adjacent counties not experiencing a natural disaster during this seven-month event window.[17] For every natural disaster, we exclude counties that were affected by any other disaster within the window. A branch's deposit rate before (after) the disaster is the average over the first (last) three months. To account for the delay in banks' adjustment to the Federal Funds rate, we construct the rate change as the difference between the Federal Funds rate one month after the disaster and the rate three months before the disaster.[18] We obtain the social connectedness index for each disaster event for any two counties in both treatment and control groups.

We match the monthly disaster data with quarterly bank-level data when combining the different variables. Due to the differences in the frequency of the data, when the disaster takes place in a particular month, we use the bank-level information as of the preceding quarter. Also, we match our branch sample with the disaster sample based on county location. We exclude disasters with no branch observations in either treated or controlled counties to ensure enough variation. We also remove disasters in counties where all branches are either rate-setters or rate-takers. Thus, we ensure at least one rate-setter and one rate-taker branch exist in the treated and control counties for each disaster. We also exclude one state-wide natural disaster, Hurricane Sandy in 2012, due to its wide coverage across almost 24 states.[19] Our final sample consists of 264 disasters from October

[17] To define adjacent counties, we follow the 2010 version of definition from the US Census Bureau. See https://www.census.gov/geographies/reference-files/2010/geo/county-adjacency.html.

[18] Recall that pre-disaster and post-disaster deposit rates are defined as the average rates within the three months before and after the disaster. Therefore, we choose the pre-period of the Federal Funds rate (FFR) as the starting month of the 3-month pre-period. Similarly, we choose the post-period of FFR as the starting month of the 3-month post-period. The change is defined as postFFR minus preFFR.

[19] Due to the extensive reach of Hurricane "Sandy" and its influence on numerous counties, we find ourselves lacking

2008 to December 2017. As the spatial analysis requires valid locational information of the branches, we further exclude branch observations with no unique identification number and/or location information. After excluding branches with missing data for the main variables mentioned in Section 3.1, our final sample contains 47,388 disaster-branch pairs.[20]

3.3. Descriptive evidence

Panel A of Table 1 presents the summary statistics for the variables used in the empirical work. This table shows there is substantial variation in the variables. The sources for all variables and their descriptions can be found in Table A.1. In Panel B of Table 1, we compare the deposit-rate setter and deposit-rate taker branches. The mean values of all variables in this table are significantly different for the two types of branches. It shows that nearly 80 percent of the rate-setter branches belong to banks with less than $2 billion in assets. It is consistent with the deposit-rate difference between the two groups: the rate-setter branches have significantly higher deposit rates than rate-taker branches, with a difference of 30 basis points, as small banks offer higher deposit rates to compete with large banks. Even though there are statistically significant differences for most other variables, the economic differences are relatively small.

[Table 1 About Here]

4. Empirical specification and results

a sufficient number of neighboring unaffected counties to perform our empirical analysis.

[20] We appreciate the input from the two anonymous referees who highlighted the distinction in the structure of our sample compared to conventional panel datasets. Instead of relying on a balanced data panel, we followed Dlugosz et al. (2022) to focus only on the short periods surrounding each disaster and compile a sample of stacked event studies. It is difficult to explain/focus on the effect of disasters due to a number of confounding factors, for instance, regional demographics and economic activities such as entry, exit, and mergers in retail banking, when we use the full raw panel data. In addition, the raw panel data from Ratewatch contains millions of observations of monthly deposit rates at the branch level during our sample period, which makes the empirical analysis intractable. We believe our sampling approach is efficient and effective, without sacrificing key empirical content. Moreover, it is worth noting that this approach has also been employed by other studies investigating the impact of natural disasters, e.g., Allen et al. (2022) and Petkov (2022). A similar approach is also employed in classical literature, such as Card and Krueger (1994).

This section first illustrates the non-spatial pattern of deposit rate changes following the traditional difference-in-differences (DID) technique. We then apply the spatial model framework to empirically study potential spillover effects of natural disasters on the change in deposit rates of branches in affected counties relative to those in neighboring counties.

4.1. Non-spatial framework

We first examine the impact of natural disasters on bank deposit rates. To accomplish this, we employ a traditional difference-in-differences (DID) framework, which compares deposit rates before and after the occurrence of a disaster. More specifically, we utilize an event-study specification by analyzing a sample of stacked average deposit rates over a period of three months prior to and following natural disasters.[21] The regression model is:

$$\Delta R_{i(c)d} = \beta_0 + \beta_1 \text{Treatment}_{cd} + \beta_2 \text{RateSetter}_i + \beta_3 \text{Treatment}_{cd} \times \text{RateSetter}_i + \beta_4 \text{Controls} + \gamma_c + \epsilon_{id}, \tag{6}$$

where $\Delta R_{i(c)d}$ is the post-pre difference in the change of the deposit rate ($\Delta R_{i(c)d} = R_{i(c)d}^{post} - R_{i(c)d}^{pre}$), for branch *i* in the county c of natural disaster event d. "$Treat$" $_{cd}$ is a dummy variable that takes the value of 1 for branches in county *c* that was affected by the disaster event *d*, and 0 if county *c* is not affected. "$RateSetter$" takes the value 1 if the branch *i*'s deposit rate is set within the county, and 0 otherwise, and γ_c is the county fixed effect.[22] The control variables include deposit-asset ratio, equity capital ratio, an indicator for a small bank, an indicator for the local market, an indicator for the important market, log of the total population, log of median income,

[21] This specification also strictly follows Dlugosz et al. (2022).

[22] Instead of focusing on the typical DID framework, we employ a modified version of DID, which could be viewed as a triple difference model. The first difference is the dependent variable change in deposit rates (rates three months after a disaster minus rates three months before the disaster), which enables us to capture the "post" effect resulting from the disaster. The second difference is "Treat," which allows us to examine the difference between affected and unaffected counties. The third difference involves the introduction of the variable "RateSetter," which enables us to highlight the difference between rate-setter branches and rate-taker branches in terms of their spillover effects on the entire banking system.

MSA indicator, percentage share of the black population, and percentage share of college and above graduates.[23]

The results of a traditional non-spatial DID model are reported in Table 2. We present the results with no control variables in odd columns and those with additional control variables in even columns. In line with the findings of Dlugosz et al. (2022) and our theoretical model, our analysis reveals positive and significant coefficients for the interaction terms. This suggests that following a natural disaster, branches exhibit an increase in their deposit rates. Furthermore, we conduct a Moran test on the residuals and reject the non-spatial null hypothesis in all cases, thus motivating and supporting the spatial framework.

[Table 2 About Here]

4.2. Spatial model framework

The non-spatial DID approach is widely used in examining the impact of natural disasters on financial institutions. As Berg et al. (2021) state "…spillover effects are often ignored in firm-level analyses, even though they are highly plausible in these settings." The existence of spillover effects implies that the stable unit treatment value assumption (SUTVA) is violated and leads to biased results.[24] As the theoretical framework implies a strategic interplay of branches in determining deposit rates in local markets, we employ a spatial DID approach to empirically measure both the direct and indirect impacts of natural disasters, unlike the approach taken in the previous literature (Klomp, 2014; Schüwer et al., 2019; Nguyen and Wilson, 2020; Dlugosz et al., 2022).

[23] Level measures of total assets, total deposits, and total equity capital are not included in the empirical estimation, since they largely overlap with the proportion/ratio measures, and we believe that the proportion/ratio measures contain relatively more information. However, the results still hold when including the level measures.

[24] Berg et al. (2021) also suggest "… adding (industry or region) fixed effects can worsen the problem. As fixed effects estimators focus on within-group variation, any bias induced by spillovers within an industry or within a region can be amplified with fixed effects estimators."

Motivated by local competition channel in our theoretical model, we consider two categories of spatial networks to capture the spillover channel among banks.[25] First, we account for a bank's physical presence at the county level. The weight between branch *i* and branch *j* is defined by the share of branches owned by *j*'s banks in the county, or:

$$W_{ij} = \begin{cases} \frac{\text{Number of branches owned by branch j's bank in the county}}{\text{Total number of branches in the county}}, & \text{branch i and j in the same county} \\ 0 & \text{otherwise.} \end{cases}$$

We next use the geographic distance between two branches *i* and *j* to describe the network structure. Two branches are geographically connected only if the distance is less than a threshold. We define the preferred threshold as equal to 30 miles, following Abrams (2020).[26] We also vary the distance threshold by setting it equal to 20, 40, and then 60 miles as a robustness check in Section 7.2 on the consistency in the pattern of spillover effects of natural disasters.[27] Table 3 shows the descriptive patterns of the spatial weighting matrix at different distance threshold levels. We compare the density of the spatial weighting matrix measured by the number and percentage of neighboring branches out of the total number of branches for each disaster with different distance thresholds. The number of branch neighbors shows significant heterogeneity as we vary the size and connectedness of the spatial weighting matrices across various disasters. The average number of neighboring branches is consistently greater than the median number, which is consistent with the uneven geographical distribution of branches—densely in metropolitan areas and less concentrated elsewhere. Using our preferred 30-mile threshold, we find that, on average, each branch has neighboring branches that account for more than one-third of all branches in the

[25] The actual weighting (distance, deposit and social connectedness) can be interpreted in numerous ways beyond just local competition. Our current study leaves the exact channels open while focusing on capturing the presence of the indirect impact. We leave it to future research to disentangle those channels with more granular data. We thank the anonymous referee for highlighting this perspective.

[26] Abrams (2020) finds that the maximum distance between the centroid of a census tract and a bank's nearest branch is on average about 30 miles.

[27] All spatial weighting matrices are row normalized.

spatial network, and almost half of the neighboring branches are in a different county. The general pattern is that the spatial network becomes more connected as the distance increases, implying a larger proportion of links between branches in different counties.[28] The overlapping of counties in branches' local networks signifies potentially significant spillover effects between counties when local conditions in some parts of the geographical market exogenously change due to a natural disaster.

[Table 3 About Here]

We then incorporate a spatial model framework within the DID approach. Specifically, we introduce the spatial lag model (SAR) to capture the potential spillover effects on deposit rate changes. The SAR-DID specification of branch *i*'s deposit rate change from the pre- to post-period of disaster d in county c is:

$$\Delta R_{i(c)d} = \rho W_i \Delta \mathrm{R}_d + \beta_0 + \beta_1 \mathrm{Treatment}_{cd} + \beta_2 \mathrm{RateSetter}_i + \beta_3 \mathrm{Treatment}_{cd} \times \mathrm{RateSetter}_i + \beta_4 \mathrm{Controls} + \epsilon_{id}, \quad (7)$$

where W is the spatial weighting matrix, based on one or the other of the two definitions of spatial networks, and W_i is the *i*th row of W, and $\Delta \mathrm{R}_d$ is the vector of deposit rate changes of all branches in the spatial network of disaster event d.

4.3. The role of social distance

Rehbein and Rother (2020) point out that, beyond the physical and cultural distance, social connectedness between counties can serve as an information channel affecting a bank's lending behavior. In particular, rate-setters in counties that are more closely connected to those in affected areas may adjust their deposit rates more effectively and responsively than counterparts in less socially connected counties. At the same time, households in unaffected areas may be influenced

[28] We do not present summary statistics for the two alternative weighting matrices because each row is the same in these two cases.

by their family and friends in affected areas, and, therefore, change their deposit behavior. To capture the intensity of information exchange among depositors in counties, we introduce the social connectedness weighting matrix in this section.

We estimate a partial-spatial Durbin model (SDM) that allows the effect of natural disasters to spill across counties through the information channel among depositors. The advantage of the partial-SDM framework is that it can simultaneously capture the effects of the spatial and social networks. We denote *W2* as the weighting matrix based on the Facebook social connectedness index. We set the social connectedness distance within the same county as zero[29], therefore zero for the corresponding element of two branches located in the same county in $W2$. We assume that disaster information spreads rapidly across all parts of the county, and the spillover via this information channel only occurs between different counties. After row normalization, the weights of social connectedness distance between two branches in different counties are obtained from the index between these two counties.

$$W2_{ij} = \begin{cases} \dfrac{\text{Social Connectedness Index between branch i and j's counties}}{\text{Sum of Index of branch i's county to all other counties}}, & \text{branch i and j in different counties} \\ 0 & \text{branch i and j in the same county.} \end{cases}$$

The reasoning behind this approach is that branches in the same county should receive the disaster shock simultaneously, while branches in adjacent counties may respond differently via the social network channel[30]. Thus, we build up a partial-SDM with two different weighting matrices, one for the treatment variables and the other for the change in the deposit rate, as follows:

$$\Delta R_{i(c)d} = \rho W1_i \mathbf{\Delta R}_d + \beta_0 + \beta_1 \text{Treatment}_{cd} + \beta_2 \text{RateSetter}_i + \beta_3 \text{Treatment}_{cd} \times \text{RateSetter}_i + \beta_4 Controls + \beta_5 W2_i \boldsymbol{Treat_d} + \epsilon_{id}. \quad (8)$$

The sign of β_5 captures the competing effect between spatial and social spillovers and $\boldsymbol{Treat_d}$

[29] As pointed out in Bailey et al. (2018), the social connectedness of a county is often strongest with other counties within the same state, even compared to nearby counties in other states.
[30] Bailey et al. (2018) suggest "…a significant correlation between social connectedness and knowledge spillovers, innovation, and, ultimately, economic growth".

is the vector of $"Treat"_{cd}$ for all branches in the network of disaster event d. We expect the social connectedness weighting matrix to expand the branches' competition network beyond the local geographic sphere. A positive sign of this coefficient indicates the spillover effects via an information channel between counties, consistent with the findings of Cortés and Strahan (2017) that deposit rates increase in neighboring branches after a disaster.

4.4. Spatial and social spillover effects

Table 4 describes the main results for the spatial regression specifications. We find strong spatial correlations in all specifications, and the non-spatial linear model is firmly rejected based on the Moran test on the residuals. The autocorrelation coefficient is sizable and statistically significant. The magnitude of spatial autocorrelation suggests that changes in deposit rates due to the indirect effect of branches in the local network account for about 70% of total changes in deposit rates. In terms of the social spillover effects, the coefficients for the lag treatment in Table 4 are significantly positive, except in the case where we use a 30-mile threshold and include control variables. The result suggests that there is a substantial positive spatial correlation across socially connected counties when the local geographic connection is confined within the same county, as in the first category of network definitions, but to a lesser degree as the geographic network expands. This finding, moreover, suggests that branches compete across counties, possibly via the information channel. Ignoring the spatial spillover pattern leads to an understatement of the connection among branches and an overestimate of the role of other explanatory variables, such as the change of the Federal Funds rate.

[Table 4 About Here]

Estimates of the interaction between rate-setter branches and the disaster indicator are significantly positive across all specifications. The positive sign is consistent with the prediction from the theoretical model that the rate-setter branch has an incentive to raise the deposit rate when the local area is adversely affected by natural disasters.

5. Interpretation of spillover effects

In this section, our focus lies on examining the spillover effects and breaking them down into two distinct components: direct impacts and indirect impacts. Furthermore, we present supporting evidence on the role of local competition as one of the key driving forces behind the spillover effects.

5.1. Direct and indirect impacts

The important value of our spatial DID framework is that we can further decompose the total treatment effect into the direct and indirect effects (LeSage and Pace, 2009). However, due to the non-linear nature of the spatial model framework, one needs to be cautious when interpreting the treatment effects of disasters. Following the standard spatial literature (e.g., LeSage, 2008; Anselin and Bera, 1998), we first show the direct, indirect, and total impacts of each main variable in Table 5. These impacts measure how an incremental change in one variable affects the outcome of the unit itself (direct impact), the average outcomes of its neighbors (indirect impact), and the sum of the two effects (total impact). For all scenarios, we obtain a larger magnitude of the indirect impact than the direct impact, and the indirect impact accounts for at least 64% of the total impact.

[Table 5 About Here]

However, given the interaction term between the disaster and rate setting in the DID framework, evaluating the effects of the disaster shock or the rate setting for deposit rate changes requires combining the main effect with the interaction term. Therefore, we calculate the following effects based on results from Table 5: (i) focusing on rate-setters, we obtain the impacts of disasters on deposit rates set by them by comparing rate-setters in treated and control counties; and (ii) similarly, we compare the difference in deposit-rate changes between rate-setters and rate-takers within the affected counties. These two effects are again further decomposed into direct, indirect, and total effects, respectively.

We design a relatively efficient algorithm to calculate direct, indirect, and total effects when using two different spatial weight matrices for the partial-SDM.[31] We use the Delta method to calculate the corresponding standard errors of these impacts accounting for the covariance matrix of coefficients. To ensure no spatial correlation remains, we conduct Moran tests on residuals obtained from all the regressions.

As shown in Table 6, the direct effects of disasters on rate-setters are around 1.5 basis points in all specifications, close to the estimated coefficients of the interaction term. The positive direct impact of the natural disaster confirms *Hypothesis 1* of the theoretical model. By comparison, indirect effects due to the propagation from other branches across the network structure at least double the direct effects in magnitude, ranging between 2.7 and 4.3 basis points, which also supports the local competition effect in *Hypothesis 2*. On average, the total effect of disasters on the affected rate-setter branches amounts to a 5 - 7 basis point increase in the deposit rate, almost equivalent to the effect of about a 20-basis point increase in the Federal Funds rate given the estimation result of a non-spatial linear model with full control variables. These causal effects are also statistically significant for all spatial specifications. In contrast, we do not find significant differences in the deposit rate changes between rate-setters and rate-takers in affected areas. One potential reason is that the rate-setters for branches in unaffected counties are located in

[31] The standard R package for spatial regression "Spatialreg" does not allow two different weighting matrices in reporting direct and indirect impacts in the partial Spatial Durbin model, and we follow LeSage and Pace (2009) to obtain the point estimation of these impacts and their standard errors. Details of derivation are available upon request.

the treated counties. Overall, this decomposition exercise reveals substantial and non-negligible indirect effects of natural disasters on branches' rate-setting behavior due to spatial spillover effects.

[Table 6 About Here]

5.2. Model comparison

We conduct likelihood ratio tests to compare the baseline SAR with partial-SDM and several versions of autoregressive weighting matrices W1. We find clear statistical evidence favoring the partial-Spatial Durbin model that incorporates an additional social connectedness weighting matrix on the treatment (Table A.2). Our results suggest that spillovers via social connectedness across counties still play a significant role in the change of branch deposit rates due to disasters, even after we include all control variables. Unsurprisingly, as the distance threshold rises in W1, the increased number of geographically connected branches across counties results in a less significant effect on the social information channel, which is consistent with the strong negative correlation between geographic distance and the social connectedness index for two counties. Bailey et al. (2018) also found strong negative correlations between distance and social connectedness.

5.3.Spillover effects and competition

We also explore the relation between branch-level indirect impacts and local market competitiveness measured by the county-level Herfindahl–Hirschman index (HHI). The indirect impact of natural disasters at one branch level is the average impact of rate changes from all neighboring branches in the area. The HHI is calculated by the sum of the squared deposit shares of branches within the county. As shown in Table 1, the minimum HHI for the sample is 0.05, corresponding to 20 branches with equal deposit shares (0.05) in a county, while the maximum

HHI is 1 for the monopoly case. We run the linear regression of all branches' indirect impacts on the HHI of their located counties. Based on the regression findings presented in Table 7, a shift in market concentration from a monopoly to the observed minimum level is associated with a projected increase of 1.3 basis points in the indirect effects on deposit rate changes for all branches. Considering the average indirect effect is 4.11 basis points, this increase counts approximately 30 percent of the average indirect effect across all branches. In the case of rate-setting branches alone, this increase could be even more substantial, potentially reaching 50 percent of the average indirect effect.

Though we are unable to empirically examine all potential channels for the spillover of deposit rates due to data limitations, these findings do highlight a relatively large indirect impact of local competition among branches. Specifically, branches in highly competitive local markets tend to respond more to neighboring branches' rate adjustments, despite not being necessarily directly impacted by the natural disaster.

[Table 7 About Here]

6. Heterogeneity analyses

The results discussed previously are based on the assumption that all bank types experience the same treatment effect when affected by disasters and face the same level of spatial competition. However, depending on a bank's characteristics, one might expect some degree of heterogeneity in response to both effects. Thus, in this section, we present new evidence to evaluate the heterogeneity in the spatial correlation that measures the level of the spillover effects of deposit rate changes, as a proxy for branch's responsiveness to local competition. We study how deposit rates change differently, depending on whether the bank is digitally advanced, whether the bank operates only in one county, and whether the local market is concentrated.

To explore heterogeneity in spatial correlations that measure the level of the spillover effects of both the rate change and a disaster – as a proxy for local competition intensity-- we use a two-order spatial model based on the partial-spatial Durbin model of Guo and Qu (2022). The model is specified as follows:

$$\begin{gathered}\Delta R_{i(j)d} = \rho_1 D_i(W1_i \boldsymbol{\Delta R_d}) + \rho_2(1 - D_i)(W1_i \boldsymbol{\Delta R_d}) + \beta_0 + \beta_1 Treat_{dc} \\ +\beta_2 RateSetter_i + \beta_3 Treatment_{dc} * RateSetter_i + \beta_4 D_i(W2_i \boldsymbol{Treat_d}) \\ +\beta_5(1 - D_i) * (W2_i \boldsymbol{Treat_d}) + \beta_6 Controls + \epsilon_{id\,,}\end{gathered} \tag{9}$$

where D_i is the binary indicator of "Online Bank" or "One County Bank" or "High Concentrated Market" for branch *i*.

6.1.Online bank

Motivated by Nguyen (2021), who argues that online banking services function as a cushion to mitigate the adverse effects caused by branch closures, we focus on online banks as the source of heterogeneity. We construct a measure for online services based on the value of data processing expenses, telecommunications expenses, as well as whether there exist additional expenses related to the presence of a transactional website, since data processing expenses may proxy for the bank's choice in technology investment (Sedunov, 2017). We did not consider the independent effect of having a transactional website, since, as of 2008, roughly 90% of all banks have a website, and 86% have an interactive website (Sedunov, 2017). Instead, we construct the measure by combining the expenses and website information from FDIC Call Reports. The data processing expenses are obtained by dividing data processing expenses by a bank's total assets. We follow the same procedure to construct the telecommunications expenses, which is the share of telecommunications expenses relative to total assets.[32] We sum the data processing and

[32] Note, for data processing and telecommunications expenses, banks need only report them if the value exceeds a certain threshold. This means that a value of zero for these expenses does not indicate that there are no such expenses, but rather that the expense is too low for reporting purposes. More specifically, reporting thresholds for data on the two variables are as follows: for 2008Q1-2016Q2: greater than $25,000 that exceeds 3% of other noninterest expense; and for 2016Q3-2018Q1: greater than $100,000 that exceeds 3% of other noninterest expense. Such a reporting rule should not invalidate the indicator because the ranking at the top quantile would unlikely be affected.

telecommunications expenses for each bank and multiply the total expense by the indicator of having a transactional website as the measure for online services. We then rank banks every quarter and construct the indicator of "Online Bank" according to the top quartile of the measure described. It is set equal to 1 if a particular bank belongs to the top quartile, and 0 otherwise.

Another aspect of heterogeneity is related to the declining number of banks that only operate within one county. As shown in Table A.3 and Figure A.2, there is a decreasing trend for the number of banks that operate in only one county within disaster-affected counties in the U.S., whereas the number of multi-county branches remains relatively stable over the years. These highly localized banks could play a crucial role in providing financial services in under-represented areas that larger banks may not serve.[33] The decline in the number of their branches may limit the financial resiliency of local communities facing negative shocks such as natural disasters. Due to the lack of access to multiple markets, one-county banks may be more inflexible to internal "smoothing" of the adverse effects caused by disasters. In this case, one might expect these banks to be more affected if they are in disaster-affected counties compared to those that operate in multiple counties. We further explore the heterogeneous responses for banks that operate in only one county to test the hypothesis. Moreover, we study the heterogeneity in spatial correlation to explore the heterogeneity in local competition intensity for the one-county banks.

Advances in the information technology used by the banking industry arguably have altered local competition among branches. On the consumer side, access to regular banking services through a mobile app or a website makes the distance to a branch less important in obtaining a banking service. On the bank side, more digital investment in banking operations also reduces the reliance on a network of brick-and-mortar operations and enables a bank to better smooth local external shocks across wider regions. Branches operated by more digitalized banks should attract a different mix of customers than less digitalized banks.

[33] Of the 5,011 banks in 2017, 2,018 operated in only one county, of which 963 had no branches.

As a result, the branches of digitalized banks should pose less competition with nearby branches of the less digitized banks. This difference in types of branches should create a smaller spillover effect than would occur if the branches were operated only by less digitalized banks. Indeed, the spatial correlation estimated for branches from the top 25% of banks in digitalization ranking has half the coefficient size for the remaining branches, as shown in Columns 1 and 2 of Table 8, and such difference is also statistically significant at 1% level. In addition, we find a greater response from more online-oriented banks to a disaster in the neighboring counties via the information channel, which is consistent with an information advantage for digitally advanced banks.

[Table 8 About Here]

6.2.One-county bank

Columns 3 and 4 in Table 8 show heterogeneous spatial spillovers for a one-county bank. A key finding is that the information channel via social connectedness significantly contributes to a one-county bank's response to disasters in adjacent counties. Competition intensities are quite similar for one-county and multi-county banks once we account for the social spillover. However, the significant positive coefficient of the spatial weighted treatments for one-county banks suggests that these banks expand their service range by raising deposit rates to attract funds from neighboring areas even beyond the specified distance threshold. Doing so may allow them to mitigate a funding constraint due to their limited physical presence in the local deposit market and better smooth their internal fund flow. Hence, one-county banks respond more to local market conditions than larger banks operating across multiple counties or nationwide.

6.3.Market concentration

Columns 5 and 6 in Table 8 provide evidence of heterogeneity for spatial correlations under different degrees of the market concentration. We group branches into low concentration markets if the county-level HHI is below the median level in the given year, and high concentration markets if the county-level HHI is above the median level in the given year. In both SAR and SDM, branches in markets with the dense distribution of competitors show a significantly (p-value=0.000) larger spatial correlation than those in less concentrated counties. This result is consistent with the local competition channel for the spatial spillover. We also find that branches facing more competition tend to raise their deposit rates more through informational channels measured in the social connectedness than those in less competitive markets.

7. Robustness checks

7.1.Alternative spatial Durbin models

Our main equation (7) uses the 30-mile threshold to construct the spatial autoregressive weighting matrix and the social connectedness for the Durbin term. We consider that most depositors only search for branches within some physical distance (e.g., 30 miles), and banks might not heavily rely on social media to disperse the change of deposit rates. The informational channel would probably play a bigger role in spreading the local disaster event than promoting branches' deposit rates to attract distant customers during our sample period. Nonetheless, there are other valid candidates for W1 and W2 under similar reasoning. Table A.4. includes 9 specifications of W1 and W2 for the robustness check. The estimation results of the key variable of interest, the interaction of treatment and rate setting, are stable and consistent over these specifications. Given all estimated coefficieints we repeat the calculation in Table 6 for each specification, and we find total effects of treatment are similar**.** Using the distance threshold outperforms the number of the same bank's branches and the social connectedness as W1's candidate, and our main equation (7) has the largest log likelihood among all.

7.2. Alternative definition of weighting matrix

As a robustness check, we first vary the distance thresholds to 20, 40, and 60 miles and explore the pattern of the spatial spillover effects. As shown in Table A.5, the estimates of parameters of interest are robust to the different thresholds across different specifications. Furthermore, when the network is constructed by geographical distance, the intensity of spatial correlation increases when the threshold distance increases. However, the spillover effects become insignificant once the network is based on the geographical distance threshold. It is plausible that the increase in distance threshold allows more neighbor branches from adjacent counties into the local competition network, which then overlaps with the role of social connectedness.

We then apply a similar definition of weight matrix W1 but replace the number of branches with the deposit volume of branches within the same county. Specifically, the weight is:

$$W_{ij} = \begin{cases} \frac{\text{Deposit volume of branch } j\text{'s bank in the county}}{\text{Total deposit volume of all branches in the county}}, & \text{branch i and j in the same county} \\ 0, & \text{otherwise} \end{cases}$$

Based on these weights, we obtain very similar results to those based on weights using the number of branches.

7.3.Alternative deposit products

In addition to the 12-month CD deposit rate, we also explore the effects on other two-CD products, namely, the 6-month and 24-month CD deposit rates. We apply the two definitions of spatial networks in Section 4 and consider the spatial autoregressive- and partial-spatial Durbin model with all control variables. As shown in Table A.6, the sign of key parameters is consistent with the finding with 12-month CDs. Also, we find the magnitude of estimates using 24-month CD deposit rates are quite close to the results for the 12-month CD, while the change of the 6-month CD deposit rates is less so. Lastly, we obtain a large positive and significant coefficient for the social connectedness with 24-month CD rates, suggesting banks may prefer to promote longer maturity products to lower liquidity risk in response to a disaster.

7.4. Other confounding factors

To alleviate concerns of time-trend and location-specific confoundedness,[34] we add a time-varying group effect to control for a branch's location in a coastal county or metropolitan area.[35] Each group is defined as a unique year-coastal-metropolitan combination. As shown in Table A.6, the results remain highly robust and consistent regarding the parameters of interest despite a relatively smaller spatial autocorrelation, which is expected since these group-specific terms absorb some of the correlations of rate changes between branches within the same group.

8. Conclusion

We present new and novel empirical evidence of both direct and indirect impacts of natural disasters on deposit rate changes made by bank branches in U.S. counties following natural disasters from 2008 to 2017. Our empirical findings are consistent with the hypotheses on the positive effects of natural disaster shocks and local competition effects on a branch's deposit rates. The estimation results indicate that natural disasters' indirect spatial spillover effects, which are not considered in previous studies, contribute substantially more to deposit rate changes than the direct effects, which are considered. Specifically, compared to branches setting deposit rates in the unaffected adjacent counties, rate-setters in affected counties on average raise their deposit rates by 1.5 basis points directly from the disaster shock, while indirect effects contribute to an additional increase between 2.7 and 4.3 basis points for all branches in the local market. We also confirm that the spillover effects occur among branches across counties, via both the social connectedness and the geographical network, while mainly depending on the latter as the distance threshold increases.

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[34] Other fixed effects, such as county or bank level, are too high-dimensional and computationally infeasible in the maximum likelihood estimation for the spatial model.

[35] The definitions are based on the official Census Bureau definition. Formal data links are as follows: Metro: https://www.census.gov/programs-surveys/metro-micro/geographies/geographic-reference-files.html; and Coastal: https://www2.census.gov/library/stories/2018/08/coastline-counties-list.xlsx.

Advances in information technology in the banking industry have undoubtedly changed the local competition among branches. Thus, as a further check on our results, we focus on online banks rather than all banks, allowing for a heterogeneity analysis. We find the spatial correlation estimated for the branches of online banks has half the coefficient size for the remaining branches. Also, we find a greater response from more online-oriented banks to a disaster in the neighboring counties via the information channel, reflecting a possible information advantage from digitally advanced banks. The social connectedness, moreover, provides an effective information channel for one-county banks to reach adjacent counties by raising deposit rates in response to natural disasters. Branches in more competitive local markets are more responsive to others' rate changes and disasters via the informational channel.

Our new and novel results indicate that failing to account for spatial spillover effects can substantially understate the impact of shocks to local markets on deposit rates of branches in both affected and neighboring communities. Our study is one of the first to capture the spatial spillover effects of natural disasters on the deposit rate setting of branches based on their geographic distance from those branches in counties directly exposed to such disasters. Also, we introduce new social connectedness data to test the potential differential geographical and social spillover channels inducing deposit-rate adjustments after a natural disaster. Finally, we contribute evidence to better understand the overlooked role spatial competition among branches plays in multimarket rate-setting changes due to shocks in local deposit markets. We theoretically motivate our empirical findings by a multi-market rate-setting competition model. Nonetheless, it is worth further study on testing or quantifying alternative mechanisms underlying the spillover pattern of retail banking pricing decisions, which is crucial for understanding the complex market structure of retail funding markets. We leave it to future research when richer data becomes available.

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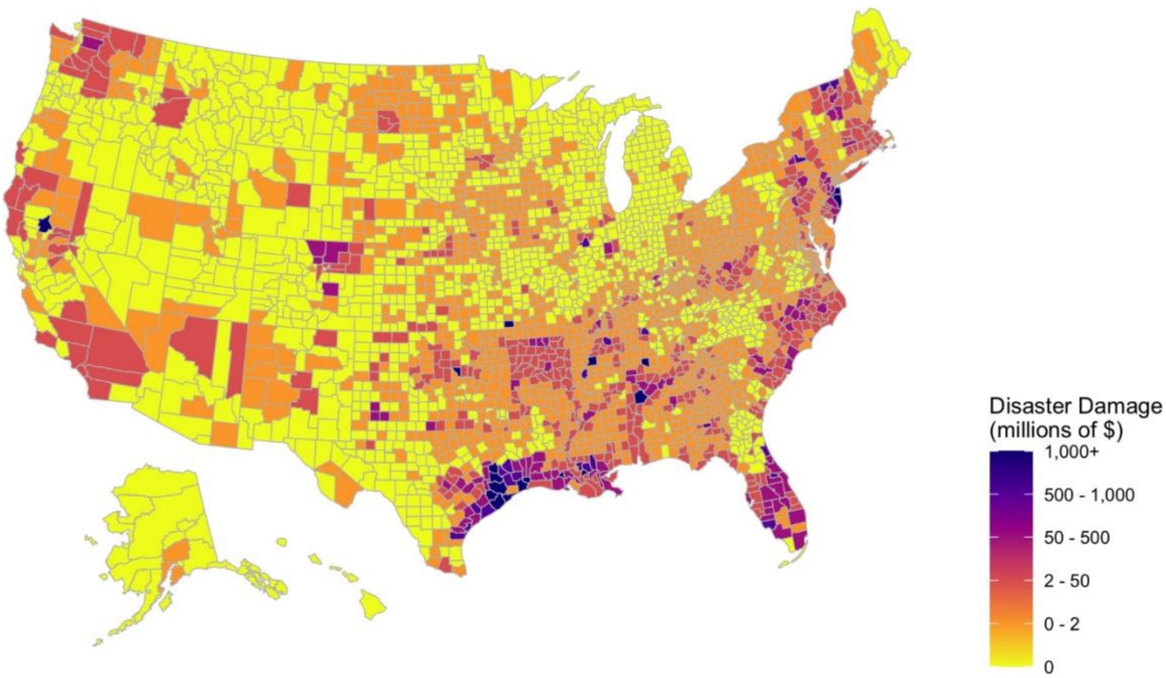
Figure 1. Damages due to natural disasters at the county level, 2008-2017



Note: This figure presents the county-level pattern of damages due to natural disasters from 2008 to 2017. Data sources are from FEMA and SHELDUS.

Table 1. Summary statistics

Panel A. Summary statistics for variables used in the estimation

	Obs.	Mean	Min	Max	Median	Std. Dev.
12-month CD rate, %	47,388	0.42	0.01	3.99	0.25	0.49
1(RateSetter)	47,388	0.10	0	1	0	0.30
1(Treatment)	47,388	0.48	0	1	0	0.50
Total assets, $billions	47,388	350	0	2,152	16	620
Total deposits, $billions	47,388	256	0	1,540	12	449
Total equity capital, $billions	47,388	36	-0.01	212	1.79	62.42
Total loans and leases, $billions	47,388	175	0	949	10	292
1(MSA indicator)	47,388	0.81	0	1	1	0.39
Deposits/assets	47,388	0.79	0.05	0.98	0.79	0.07
Equity capital ratio	47,388	0.11	-0.01	0.93	0.11	0.03
1(small)	47,388	0.34	0	1	0	0.47
1(local market)	47,388	0.15	0	1	0	0.36
1(important market)	47,388	0.35	0	1	0	0.48
HHI	47,388	0.19	0.05	1	0.15	0.12
Ln(county population)	47,388	12.27	6.49	15.48	12.38	1.57
Ln(county median income)	47,388	10.87	9.91	11.81	10.85	0.26
% black population	47,388	0.13	0.00	0.86	0.09	0.14
% population with at least college degree	47,388	0.19	0.03	0.48	0.18	0.08

Panel B. Summary statistics by branch rate group

	Rate taker	Rater setter	Difference	P-value
12-month CD rate, %	0.39	0.69	-0.30***	0.00
1(Treatment)	0.49	0.42	0.07***	0.00
Total assets, $billions	383	45	338.61***	0.00
Total deposits, $billions	280	33	247.44***	0.00
Total equity capital, $billions	40	5	35.08***	0.00
Equity capital to assets, %	11.06	10.84	0.22***	0.00
Total loans and leases, $billions	191	24	167.38***	0.00
1(MSA indicator)	0.84	0.56	0.28***	0.00
Deposits/assets	0.78	0.83	-0.05***	0.00
Equity capital ratio	0.11	0.11	0.00***	0.00
1(small)	0.29	0.80	-0.51***	0.00
1(local market)	0.11	0.54	-0.43***	0.00
1(important market)	0.31	0.73	-0.42***	0.00
HHI	0.18	0.22	-0.03***	0.00
Ln(county population)	12.38	11.30	1.08***	0.00
Ln(county median income)	10.88	10.80	0.08***	0.00
% black population	0.14	0.11	0.03***	0.00
% population with at least college degree	0.19	0.16	0.03***	0.00

Note: Panel A reports the summary statistics for variables used in estimation. We obtain demographic information from the ACS. We merge data from RateWatch, SOD, and FRED Economic Data for branch-level data. For detailed procedures for each variable's construction, please refer to Section 3. Panel B reports the summary statistics for the rate-setter and rate-taker branches. The p-values are calculated based on a t-test, with * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Table 2. Non-spatial DID results

	(1)	(2)
Treatment	0.006***	-0.002
	(0.002)	(0.002)
RateSetter	-0.025***	-0.019***
	(0.003)	(0.003)
Treatment × RateSetter	0.016***	0.013***
	(0.005)	(0.005)
Federal Fund Rate Change	0.317***	0.296***
	(0.002)	(0.003)
Control variables	No	Yes
County fixed effects	Yes	Yes
R^2	0.272	0.308
N	47,388	47,388

Note: This table presents the results of the non-spatial DID. Column (1) shows the baseline results without control variables. Column (2) shows the results with control variables, as described in Table 1 and Section 3. In both regressions, we control for county-fixed effects. Both specifications confirm a significant positive effect of disasters on the deposit rate changes of rate-setters. Standard errors are reported in parentheses. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Table 3. Summary statistics of neighboring branches across different distance thresholds

	20 miles	30 miles	40 miles	60 miles
Number of branches with zero neighbors	216	105	67	29
Percentage branches with zero neighbors	0.46%	0.22%	0.14%	0.06%
Average number of neighbors	132	173	202	246
Mean percentage of neighbors	29.80%	37.44%	43.14%	52.93%
Median number of neighbors	66	90	114	157
Median percentage of neighbors	22.05%	30.97%	37.03%	51.41%
Max number of neighbors	994	1137	1156	1192
Max percentage of neighbors	98.69%	99.81%	99.81%	99.82%
Average number of neighbors outside the county	82	110	131	166
Average percentage of neighbors outside the county	31.22%	46.35%	55.87%	65.65%
Total number of branches	47,388	47,388	47,388	47,388

Note: This table reports the summary statistics for the weighting matrix captured by the spatial distance.

Table 4. Spatial regression results

	W1: # of rival branches				W1: 30 miles neighboring branches			
	SAR w/ W1		Partial SDM w/ W2		SAR w/ W1		Partial SDM w/ W2	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	0.005***	0.001	0.002	0.000	0.000	-0.002	-0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RateSetter	-0.014***	-0.014***	-0.014***	-0.014***	-0.013***	-0.015***	-0.013***	-0.014***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Treatment × RateSetter	0.015***	0.013***	0.015***	0.013***	0.018***	0.016***	0.018***	0.016***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Federal Fund Rate Change	0.017***	0.010***	0.020***	0.011***	0.072***	0.060***	0.073***	0.060***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Lag treatment			0.012***	0.006**			0.004*	-0.001
			(0.003)	(0.003)			(0.002)	(0.002)
ρ	0.685***	0.665***	0.683***	0.665***	0.774***	0.753***	0.772***	0.754***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Control variables	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.463	0.478	0.463	0.478	0.493	0.503	0.493	0.503
ln(likelihood)	26836	27610	26839	27615	28339	28944	28331	28952
N	47,388	47,388	47,388	47,388	47,388	47,388	47,388	47,388

Note: This table presents the spatial regression results. We compare estimation results for (i) different definitions of autoregressive matrices (W1), (ii) with and without social connectedness weighting matrix (W2), and (iii) with and without control variables. We find (i) strong spatial correlation among branches as regards the change of deposit rates; (ii) disasters consistently cause setters in the affected counties to raise deposit rates; and (iii) the spillover effects across counties is significant. Standard errors are reported in parentheses. The R-squared is calculated by the formula: $R^2 = \frac{\sum_{i=1}^{n}(\hat{y}_i-\bar{y})^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2}$, where $\hat{y}_i$ the fitted value using y_i on the right-hand side of the equation being estimated. This is the standard method for expressing goodness of fit for MLE-based estimations, comparable to the least squares measure of model fit. It captures the explained variation in the dependent variable relative to its total variation. * p < 0.1 ** p < 0.05 *** p < 0.01.

Table 5. Impacts estimation

	SAR w/ W1			Partial SDM w/ W2		
	Direct	Indirect	Total	Direct	Indirect	Total
Panel A: W1: # of rival branches						
Treatment	0.001	0.003	0.004	0.000	0.016	0.016
	(0.001)	(0.002)	(0.004)	(0.002)	(0.007)	(0.007)
RateSetter	-0.015	-0.027	-0.042	-0.015	-0.027	-0.042
	(0.003)	(0.006)	(0.009)	(0.003)	(0.006)	(0.009)
Treatment × RateSetter	0.014	0.025	0.039	0.014	0.025	0.039
	(0.004)	(0.007)	(0.011)	(0.004)	(0.008)	(0.012)
Panel B: W1: 30 miles neighboring branches						
Treatment	-0.002	-0.006	-0.008	-0.002	-0.006	-0.008
	(0.001)	(0.004)	(0.006)	(0.002)	(0.009)	(0.009)
RateSetter	-0.015	-0.044	-0.059	-0.015	-0.043	-0.059
	(0.003)	(0.008)	(0.011)	(0.003)	(0.008)	(0.011)
Treatment × RateSetter	0.017	0.049	0.066	0.017	0.049	0.066
	(0.004)	(0.012)	(0.016)	(0.004)	(0.010)	(0.014)

Note: This table presents the results of impact estimation for the spatial models. Standard errors are in parentheses. We include control variables in all spatial specifications. We decompose the total impact of each variable of interest into direct and indirect effects. We find that the indirect effect of the interaction between treatment and rate-setter is substantial and significant across all models.

Table 6. Treatment effects

	SAR w/ W1			Partial SDM w/ W2		
	Direct	Indirect	Total	Direct	Indirect	Total
Panel A: W1: # of rival branches						
Treatment + Treatment×RateSetter	0.015	0.027	0.043	0.014	0.042	0.056
	(0.004)	(0.007)	(0.011)	(0.004)	(0.010)	(0.014)
RateSetter + Treatment×RateSetter	-0.001	-0.002	-0.004	-0.001	-0.002	-0.003
	(0.003)	(0.006)	(0.009)	(0.003)	(0.006)	(0.010)
Panel B: W1: 30 miles neighboring branches						
Treatment + Treatment×RateSetter	0.015	0.043	0.058	0.015	0.042	0.056
	(0.004)	(0.011)	(0.015)	(0.003)	(0.013)	(0.016)
RateSetter + Treatment×RateSetter	0.002	0.005	0.007	0.002	0.005	0.007
	(0.003)	(0.009)	(0.012)	(0.003)	(0.009)	(0.012)

Note: This table reports the interpretation of treatment effects for our spatial model regressions. Standard errors are reported in parentheses. In each panel, the first row indicates the comparison between rate-setters in disaster counties and those in unaffected counties, and the second row measures the gap in deposit rate changes between setters and takers when both are in the affected counties. The results imply that rate-setters respond significantly more to disasters in their counties than to disasters in neighboring counties, keeping their rates close to rate-takers in the same county.

Table 7. Indirect effects and competition

	All branches	Affected RateSetters
	(1)	(2)
HHI	-0.014***	-0.022***
	(0.000)	(0.002)
Constant	0.044***	0.045***
	(0.000)	(0.000)
R^2	0.032	0.060
N	47,388	1,984

Note: This table studies how competition contributes to the indirect effects of changes in deposit rates. The dependent variable is the estimated indirect effect, and the explanatory variable is the county HHI. Standard errors are reported in parentheses. * p < 0.1 ** p < 0.05 *** p < 0.01.

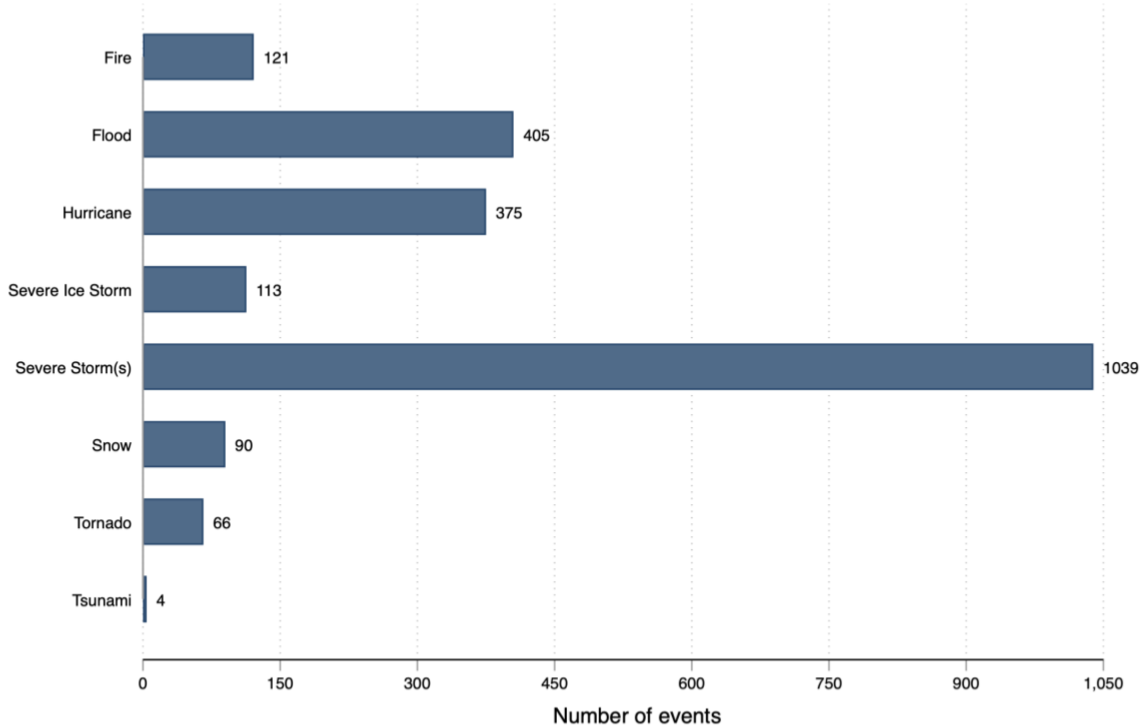
Table 8. Heterogeneity in spatial competition

	D: Online bank		D: One-county bank		D: High market concentration	
	SAR w/W1	Partial SDM w/ W2	SAR w/W1	Partial SDM w/ W2	SAR w/W1	Partial SDM w/ W2
	(1)	(2)	(3)	(4)	(5)	(6)
ρ_1	0.377***	0.382***	0.661***	0.737***	0.493***	0.481***
	(0.024)	(0.024)	(0.058)	(0.058)	(0.008)	(0.008)
ρ_2	0.787***	0.784***	0.755***	0.754***	0.902***	0.907***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Treatment	-0.002	-0.002	-0.002	-0.002	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RateSetter	-0.015***	-0.015***	-0.015	-0.015	-0.015***	-0.015***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Treatment*RateSetter	0.016***	0.016***	0.016***	0.016***	0.015***	0.015***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Federal Fund Rate Change	0.082***	0.082***	0.060***	0.061***	0.112	0.113***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
D*W2*Treatment		0.034***		0.185***		-0.021***
		(0.007)		(0.037)		(0.003)
(1-D)*W2*Treatment		0.007***		-0.002		0.005***
		(0.003)		(0.002)		(0.002)
Control	Yes	Yes	Yes	Yes	Yes	Yes
P-value ($\rho_1 = \rho_2$)	0.000	0.000	0.110	0.762	0.000	0.000
N	47,275	47,275	47,388	47,388	47,388	47,388

Note: This table presents the results for heterogeneity in spatial competition for an online bank. We compare estimation results with and without social connectedness weighting matrix (W2). D is the online bank dummy in columns (1) and (2), one county bank dummy in columns (3) and (4) and in columns (5) and (6), we create a dummy variable if the county HHI is greater than the median HHI. ρ_1 is spatial correlation for D=1 and ρ_2 for D=0. Standard errors are reported in parentheses. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

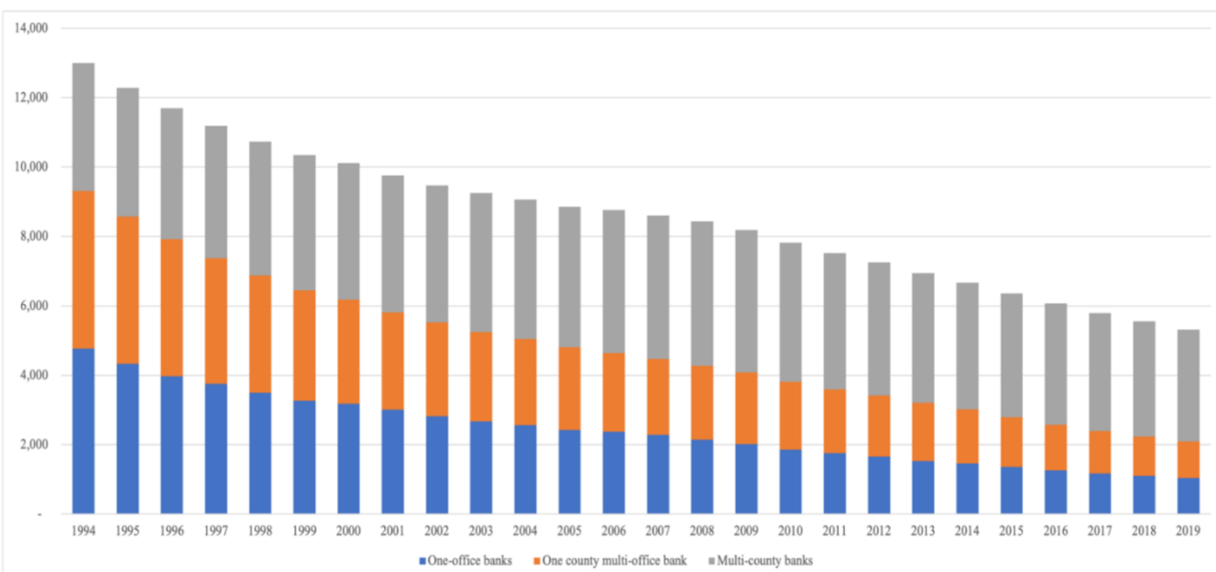
Appendix Figures and Tables

Figure A.1. Number of natural disasters by type



Data source: FEMA, SHELDUS.

Figure A.2. Number of banks and branches within disaster-affected counties



Data source: FDIC's Summary of Deposits (SOD).

Table A.1. Variable sources and descriptions

Variable	Source	Description
12-month CD rate, %	Ratewatch	Branch average monthly deposit rate of 12-month certificates of deposit with an account size of $10,000
1(RateSetter)	Ratewatch	Dummy variable equals 1 if a branch sets rates, 0 otherwise
1(Treatment)	FEMA, SHELDUS	Dummy variable indicating if a branch located county is hit by a presidential disaster
W1	Own calculation based on Summary of Deposits	$W_{ij} =$ $\frac{\text{"Number of branches owned by branch } j\text{'s bank in the county"}}{\text{"Total}}$ *numb* if branch i and j are in the same county, 0 otherwise
W1_mile	Own calculation based on Summary of Deposits	$W_{ij} = \frac{\text{Number of branches owned by j's bank within certain distance}}{\text{Total number of branches in the county}}$ if the distance between branch i and j is less than 20, 30, 40, or 60 miles, 0 otherwise
W2	Own calculation using Facebook Social Connectedness Index by Bailey et al. (2018)	$W_{ij} = \frac{\text{Social Connectedness Index between branch i and j's counties}}{\text{Sum of Index of branch i's county to all other counties}}$ if branches i and j are in different counties, 0 otherwise
Branch deposits	Summary of Deposits	Branch office deposits as of June 30
Total assets, $billions	Call report	The sum of all assets owned by a bank including cash, loans, securities, bank premises, and other assets.
Total deposits, $billions	Call report	The sum of all deposits owned by a bank, including demand deposits, money market deposits, other savings deposits, time deposits, and deposits in foreign offices.
Total equity capital, $billions	Call report	Total bank equity capital (includes preferred and common stock, surplus, and undivided profits).
Total loans and leases, $billions	Call report	Total bank loans and lease financing receivables
1(MSA indicator)	Call report	Dummy variable indicating if a bank headquarter located in a Metropolitan Statistical Area
Deposits/assets	Own calculation based on call report	Ratio of total deposits to total assets

Equity capital ratio	Own calculation based on call report	Ratio of total equity to total assets
1(small)	Own calculation based on call report	Dummy variable equals 1 if a bank with less than $2 billion in assets, 0 otherwise
1(local market)	Own calculation based on Summary of Deposits	Dummy variable equals 1 if a bank receives more than 65 percent of its deposits from the county in which it is located
1(important market)	Own calculation based on Summary of Deposits	Dummy variable equals 1 when a county ranks at the top quartile of deposits among all counties where the bank has branches
HHI	Own calculation based on Summary of Deposits	Sum of the squares of the percentage of deposits held by each of the branches in a county
Ln(county population)	American Community Survey	Log of the total county population
Ln(county median income)	American Community Survey	Log of county median household income
% black population	American Community Survey	Percent African American population
% population with at least college degree	American Community Survey	Percent of the population with a college degree or higher
Federal Funds rates	Federal Reserve Bank of St. Louis	Monthly effective Federal Funds rates

Table A.2. Likelihood ratio test

Model	P-value
Panel A: W1: # of rival branches	
SAR vs. SDMW1+W2	0.033
Panel B: W1: 30 miles neighboring branches	
SAR vs. SDMW1+W2	0.002

Note: This table reports the likelihood ratio test results for model comparison. Each panel tests the null hypothesis of the spatial autoregression model (SAR) against the alternative partial spatial Durbin model (SDM), including all control variables. We reject SAR at the 5% significance level, except for the 60-mile threshold.

Table A.3. Number of banks and branches within disaster-affected counties

Year	Number of disaster-affected counties	Number of disaster-affected counties (Bank ≥ 1)	Number of disaster-affected counties (Bank = 0)	Number of disaster-affected counties (Branches ≥ 1)	Number of disaster-affected counties (Branches = 0)
1999	506	429	77	503	3
2000	412	352	60	408	4
2001	397	346	51	396	1
2002	555	484	71	552	3
2003	745	601	144	742	3
2004	909	780	129	909	0
2005	1,082	910	172	1,078	4
2006	521	439	82	519	2
2007	527	483	44	527	0
2008	980	832	148	976	4
2009	534	427	107	533	1
2010	564	469	95	561	3
2011	965	761	204	961	4
2012	561	418	143	561	0
2013	281	230	51	281	0
2014	186	155	31	185	1
2015	475	376	99	474	1
2016	336	235	101	336	0
2017	490	347	143	487	3
Total	11,026	9,074	1,952	10,989	37

Data source: Summary of Deposits (SOD) provided by FDIC.

Note: This table describes the total number of counties affected by disaster (Column 1) from the year 1999 to 2017, among those counties, the number of counties with at least one bank headquarter (Column 2), with no bank headquarters (Column 3), with at least one bank branch (Column 4), and with no bank branches (Column 5).

Table A.4. Candidates of weighting matrices in spatial Durbin model

	W1: social W2: social	W1: social W2: distance	W1: social W2: number	W1: number W2: number	W1: number W2: distance	W1: number W2: social	W1: distance W2: distance	W1: distance W2: social	W1: distance W2: number
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment	-0.003*	0.000	-0.029	-0.092***	-0.001	0.000	-0.002	-0.002	-0.016
	(0.001)	(0.003)	(0.026)	(0.026)	(0.003)	(0.001)	(0.003)	(0.001)	(0.025)
RateSetter	-0.015***	-0.015***	-0.015***	-0.014***	-0.014***	-0.014***	-0.015***	-0.015***	-0.015***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Treatment × RateSetter	0.017***	0.017***	0.017***	0.013**	0.013**	0.013**	0.016***	0.016***	0.016***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Federal Fund Rate Change	0.059***	0.059***	0.059***	0.009**	0.010***	0.011***	0.060***	0.060***	0.060***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Lag treatment	-0.003	-0.004	0.025	0.094***	0.003	0.006*	0.000	-0.001	0.014
	(0.002)	(0.003)	(0.026)	(0.026)	(0.003)	(0.003)	(0.003)	(0.002)	(0.025)
ρ	0.829***	0.828***	0.828***	0.666***	0.664***	0.665***	0.754***	0.752***	0.754***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.489	0.489	0.489	0.475	0.475	0.475	0.501	0.501	0.501
Ln(likelihood)	28881.11	28889.73	28884.07	27611.7	27612.91	27614.78	28945.27	28952.6	28950.67
AIC	-57751.2	-57737.8	-57746.9	-55210.0	-55177.7	-55198.9	-57857.7	-57843.0	-57856.2
BIC	-57593.4	-57580.0	-57589.1	-55052.2	-55019.9	-55041.1	-57699.9	-57685.2	-57698.4
RMSE	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
N	47,388	47,388	47,388	47,388	47,388	47,388	47,388	47,388	47,388

Note: This table presents the spatial regression results using different combinations of weighting matrices. As shown in each column, the weighting matrices are defined based on the number of branches in the county, relative distance between branches, and social connectedness. The key variable of interest is the interaction of treatment and rate setter, and its estimates are quite comparable over all specifications. Total effects of treatment(disaster) and rate setters calculated based on the estimates above are also similar compared to those in Table 6. Standard errors are reported in parentheses. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Table A.5. Alternative definition of weight matrix

	W1: rival branches deposit volume share				W1: 20 miles				W1: 40 miles				W1: 60 miles			
	SAR w/ W1		Partial SDM w/W2		SAR w/ W1		Partial SDM w/W2		SAR w/ W1		Partial SDM w/W2		SAR w/ W1		Partial SDM w/W2	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Treatment	0.004***	0.000	0.000	(0.001)	0.001	-0.002	-0.001	-0.002	0.000	-0.002*	-0.001	-0.002	0.000	-0.002*	-0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RateSetter	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.015***	-0.014***	-0.015***	-0.012***	-0.014***	-0.012***	-0.014***	-0.012***	-0.014***	-0.012***	-0.014***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Treatment × RateSetter	0.015***	0.013***	0.015***	0.013***	0.018***	0.016***	0.018***	0.016***	0.017***	0.016***	0.017***	0.016***	0.017***	0.016***	0.017***	0.016***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Federal Fund Rate Change	0.038***	0.029***	0.041***	0.030***	0.084***	0.073***	0.086***	0.073***	0.064***	0.053***	0.065***	0.053***	0.053***	0.042***	0.054***	0.042***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Lag treatment			0.013***	0.007**			0.006**	0.001			0.003	-0.001			0.003	-0.002
			(0.002)	(0.003)			(0.002)	(0.002)			(0.002)	(0.002)			(0.002)	(0.002)
ρ	0.683***	0.662***	0.681***	0.663***	0.734***	0.712***	0.733***	0.714***	0.796***	0.775***	0.796***	0.775***	0.829***	0.810***	0.830***	0.810***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Control variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.471	0.485	0.472	0.485	0.488	0.499	0.488	0.499	0.494	0.505	0.494	0.505	0.495	0.505	0.495	0.505
ln(likelihood)	27203	27935	27207	27944	27936	28568	27931	28582	28516	29109	28523	29111	28745	29322	28752	29324
N	47,388	47,388	47,388	47,388	47,388	47,388	47,388	47,388	47,388	47,388	47,388	47,388	47,388	47,388	47,388	47,388

Note: This table presents the spatial regression results with varying thresholds for geographical distance. When we increase the threshold distance in the autoregressive weight matrix (W1), there is a stronger spatial autocorrelation between deposit rate changes and a decreasing social effect of disasters on rate changes. Standard errors are reported in parentheses. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Table A.6. Alternative deposit products and other confounding factors

	6-Month CD				24-Month CD				Group effects			
	W1: # of rival branches		W1: 30 miles neighboring branches		W1: # of rival branches		W1: 30 miles neighboring branches		W1: # of rival branches		W1: 30 miles neighboring branches	
	SAR w/ W1	Partial SDM w/ W2	SAR w/ W1	Partial SDM w/ W2	SAR w/ W1	Partial SDM w/ W2	SAR w/ W1	Partial SDM w/ W2	SAR w/ W1	Partial SDM w/ W2	SAR w/ W1	Partial SDM w/ W2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment	0.001	0.000	0.000	0.000	0.005***	-0.001	-0.001	-0.004**	0.002	0.002	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RateSetter	-0.005**	-0.005**	-0.005**	-0.005**	-0.015***	-0.016***	-0.014***	-0.014***	-0.011***	-0.011***	-0.012***	-0.012***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Treatment × RateSetter	0.004	0.005*	0.006*	0.006*	0.014***	0.016***	0.015***	0.016***	0.013**	0.013**	0.015***	0.015***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Federal Fund Rate Change	0.098***	0.098***	0.066***	0.067***	0.125***	0.127***	0.106***	0.107***	0.258***	0.255***	0.212***	0.210***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.008)	(0.008)	(0.008)	(0.008)
Lag treatment		0.004**		0.000		0.019***		0.010***		-0.004*		-0.001
		(0.001)		(0.001)		(0.002)		(0.002)		(0.002)		(0.002)
ρ	0.734***	0.734***	0.806***	0.803***	0.697***	0.695***	0.779***	0.777***	0.461***	0.461***	0.578***	0.580***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)	(0.008)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.576	0.576	0.584	0.584	0.534	0.534	0.544	0.544	0.502	0.502	0.507	0.507
ln(likelihood)	58176	58183	58946	58918	37157	37205	37915	37925	29477	29480	29685	29688
N	50,728	50,728	50,728	50,728	49,157	49,157	49,157	49,157	47,388	47,388	47,388	47,388

Note: This table presents the robustness checks for our main spatial regression. We compare estimation results for (i) different definitions of autoregressive matrices (W1), (ii) with and without social connectedness weighting matrix (W2). First four columns, we explore results for 6-month CD deposit rates. Second four columns, we explore results for 24-month CD deposit rates. Last four columns, we add group fixed effects. We find the result pattern remains the same. Standard errors are reported in parentheses. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.