Do natural disasters affect exposed banks differently?

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Abstract

This paper studies the heterogeneous effects of natural disasters on local banks and non-local banks. Local banks may better support communities weathering the shocks with their specialized local knowledge and relationship, but they could be vulnerable to the limited geographic diversification. Exploiting natural disasters in the US in 2018-2019, I find that natural disasters affect local banks and non-local banks differently in terms of deposit-taking and lending. Natural disasters increase (decrease) deposits supply of local (non-local) banks, leading to an increase (decrease) in deposit volume and lower (higher) deposit rate. The deposit allocation is particularly pronounced in counties with higher social connectedness. With the additional deposit supply, local banks increase more loan supply after natural disasters.

Keywords: Natural disaster, Bank lending, Credit supply, Bank deposit, Depoosit interest rate

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1 Introduction

Since the early 1900's, there had been a long-lasting discussion over unit banking and branch banking. While branch banking benefits from geographical diversification, unit banking allows banks specializing in local communities, thus more capable to provide banking services that require local knowledge and local social network. After the branching deregulation was gradually introduced from 1978 to 1992 (Kroszner and Strahan, 1999), the number of local community banks keeps declining. The number of local community banks dropped by 30 percent from 2012 to 2019.[1] In this context, the paper answers whether local banks could better weather local communities from adverse regional shocks.

In examining this question, I need regional shocks to local economies. There are two criteria for the shocks. The shocks must be unexpected and exogenous to banks' behaviours. From this perspective, natural disasters offer an ideal setting. Apart from the econometrics setting, investigating how banks respond to natural disasters gets more timely than ever. Global climate change increases the severity and frequency of natural disasters. In year 2021, about 1 in every 10 homes were impacted by natural disaster in the US. [2] Therefore, natural disaster is one of the most common regional shocks to local economy. In weathering such shock, banks play a key role. However, do all banks respond to natural disasters in the same way?

To be specified, this paper focuses on the two fundamental functions of banks, deposit-taking and lending. I examine three ex-ante uncertain questions. The first question asks whether natural disasters impact banks' deposit-taking and lending, in terms of volumes and interest rates. Second, I investigate whether local banks are affected differently.[3] Third, the paper highlights a plausible channel in driving the heterogeneous

[1]https://www.fdic.gov/resources/community-banking/report/2020/2020-cbi-study-full.pdf
[2]"https://www.cnbc.com/2022/02/17/natural-disasters-such-as-fires-hurricanes-hit-1-in-10-us-homes-in-2021.html"
[3]This paper follows Homanen (2022) in defining local banks as banks classified as savings banks, and savings and loans in the Summary of Deposits.

impacts of natural disasters on local banks.

Natural disasters increase depositors' demand of liquidity, for example the urgent need of property maintenance and medical expenses (Gallagher and Hartley, 2017; Billings et al., 2022). Therefore, depositors may withdraw their deposits in meeting the liquidity need. As a result, one would expect volumes of bank deposits decrease and deposit interest rates to increase. However, the provision of government natural disaster relief plays a role in mitigating the adverse impact of natural disasters (Strömberg, 2007; Deryugina, 2017), which may mitigate the deposit withdrawal. Thus the overall effect of natural disasters on bank deposits is ex-ante uncertain.

Disaster-exposed areas require lending to recover the damages of natural disaster, such as drawing on lines of credit to address their immediate liquidity and mortgages for property repairs. Moreover, government may motivates banks to lend after natural disasters to speed up the recovery process (Cortés, 2014). Therefore, natural disasters may result an increase in lending volumes and lending rates. However, banks may strategically reallocate their lending to unexposed or less disaster-prone areas (Ouazad and Kahn, 2022; Rehbein and Ongena, 2022), thus lowering loan supply in local area. Also deposit-loan synergies of banks could be disrupted by the deposit outflows during natural disasters (Kashyap et al., 2002; Gatev et al., 2009; Yang, 2022).

Local banks differ from non-local banks from several perspectives, including size, geographical distribution and product diversification. Local banks are smaller in terms of asset size and concentrate their businesses in local communities. Their business model is comparatively simple that they take deposits and lend within a local market. Most of the local banks have less than $1 billion in assets. Because of the geographical specification, community banks accumulates more local knowledge and soft information. Also, geographic specification of local banks may mitigate agency problems (Goetz et al., 2013). However, the lack of diversification could also cause banks to suffer from idiosyncratic risk due to the lack of product and geographical diversification (Diamond, 1984). non-local banks also benefit from economies of scales and more efficient internal capital marker (Berger et al., 1999; Houston et al., 1997). Apart from the response of banks, depositor-bank relationships and networks could also play a role. Closer bank-depositor relationship could plausibly mitigate depositors' withdrawal incentive during uncertainty (Iyer and Puri, 2012; Brown et al., 2020). Therefore, natural disasters may mitigate deposit outflows or even create deposit inflows to local banks which have a stronger social connection to local depositors.

Employing several sources of data in the US over 2018-2019, I find that, on average, natural disasters reduce the volumes of annual branch deposits by 3.36%. However, the effect is not homogeneous to local banks and non-local banks. Local banks do not experience deposit outflows following natural disaster, on the contrary, volumes of branch deposits increase by 1.84%. The paper also documents the dynamic effect of natural disasters on deposits.The impacts are short-lived and only last for 2 quarters. In terms of the pricing of deposits, natural disasters, on average, lead to 0.03% increase in 12-month certificate deposit rates, implying a reduction of deposit supply. However, the same finding could not be applied on local banks. Deposit rates of local banks reduce 0.06% after natural disasters. Contrary to non-local banks, the results imply that the additional deposit inflows are caused by an increase in supply of deposits for local banks after natural disasters, rather than an increase in deposit rates.

This paper also attempts to identify the channel in driving the deposit inflows to local banks after natural disasters. I find no evidence that bank soundness, market power and government assistance can explain the deposit inflows, but I find novel evidence that the additional deposit inflows to local banks are particularly strong in counties with higher social connectedness, highlighting the additional deposit inflows are driven by the better social connection between local banks and the communities.

In terms of lending, banks with more branches exposed to natural disasters experience stronger increase in lending, indicating the role of banks in smoothing the adverse impact of shocks on local economy. A percentage increase in proportion of branches exposed natural disaster leads to 1.51% increase in bank total lending. With the deposit inflows, local banks increase lending particularly more after natural disasters, reflecting the deposit-lending synergies and the unique role of local banks in providing liquidity to local community. For the pricing of loan, there is no evidence that natural disasters affect the interest rates of loans of non-local banks. Yet, the results suggest that local banks reduce interest rates of personal unsecured loans following natural disasters.

The paper contributes to three strands of literature. A growing strand of literature examines the impact of natural disaster risk on banks. Natural disaster potentially threat both the asset and liability side of banks (Klomp, 2014). On asset side, the most common collateral of banks, real estates, are vulnerable to extreme weather events. Therefore, natural disasters could significantly devalue the underlying assets of bank loans (Bernstein et al., 2019; Beltrán et al., 2018). Emerging evidence suggests that banks do not adequately price the climate risk into mortgages (Garbarino and Guin, 2021). Another source of less-discussed risk is the liquidity risk on the liability side. Natural disaster creates a shock to households liquidity needs, thus increases the withdrawal of bank deposits to weather the shock (Cortés and Strahan, 2017). It could therefore pose potential liquidity risk to banks. Different from the most of the existing papers which examine the 2 questions in isolation. This paper contributes to the literature by documenting the comprehensive and heterogeneous impact of natural disaster on the volumes and price of bank deposits and lending.

The paper also contributes to the literature highlighting the unique role of local banks. The key differences of community banks lie in the soft information accumulated through the banking relationship and local knowledge, which allows banks to have utilize this information in lending (DeYoung et al., 2004; Stein, 2002; Hakenes et al., 2015; Jagtiani et al., 2016; Wang et al., 2021). In the context of natural disaster, Koetter et al. (2020) find that local banks provide corporate recovery lending to firms affected by adverse regional macro-shocks. Allen et al. (2022) find that local banks increase lending to natural disaster-exposed areas, despite Allen et al. (2022) do not include non-local banks as a control group in the sample. I highlight the local knowledge and information is valuable to local community during natural disasters.

This paper also speaks to the literature on the role of social networks in economic decisions(Hong et al., 2005; Rantala, 2019; Persson et al., 2021). In the banking sector, Iyer and Puri (2012) document that the social network of a depositor affects their likelihood to withdraw during bank runs. Flynn and Wang (2022) finds that banks in areas that are more socially connected to areas recently exposed to natural disasters record an increase in bank deposits. This paper departs from the existing literature by showing how the social connectedness affect the effectiveness of local banks in weathering local economy from natural disasters.

The outline of the paper is as follows. Section 2 describes the data sources and sample. Section 3 and 4 details the identification strategies and the empirical results of the impact on bank deposits and lending respectively. Section 5 discuss the potential channels in driving the findings, and Section 6 concludes.

2 Sample and data

To ensure the findings to be timely, the paper focuses on natural disasters in 2018-2019. The study excludes observations in 2020 and 2021 because majority of the areas in the US are classified as disaster-exposed areas due to the COVID-19.

Records of natural disasters are extracted from the Spatial Hazards Events Database for the US (Sheldus). The Sheldus identifies the date and location of all presidentially declared natural disasters in the US. The paper does not examine the impact of other minor disasters, i.e., non-presidentially declared natural disasters, because the disasters in the Sheldus are more severe and represent more significant shocks to banks. The detailed record of geographical information allows me to identify banks' exposure to natural disasters. The database also details the type of the disasters. The common types of natural disasters include hurricane, severe storm and flood. Natural disasters normally last for less than a month. Figure 1 details the geographical distribution of natural disasters in 2018-2019.

To implement a throughout analysis of the impact of natural disaster on bank deposits and lending, this paper employs three data sources related to bank financial information, including the Call Report, the Federal Deposit Insurance Corporation (FDIC) Summary of Deposits, and RateWatch. The sample period covers 2018-2019.

I use the FDIC Summary of Deposits data to obtain branch-level deposits for FDIC-insured institutions, including US branches of FDIC-insured foreign banks, as of June 30th of each year. For each branch, I observe the total deposits held, the location of the branch, and the parent bank.

There are two key limitations of the SoD. The first one is the low frequency of data. It makes ruling out confounding events and identifying the dynamic effects of natural disaster difficult. Second, the SoD only contains deposit data which limits the analysis to deposits. To overcome this limitation, I turn to the Quarterly Reports on Condition and Income (Call Report) which document the quarterly bank-level data for US banks.

Finally, I employ RateWatch database to obtain information of branch-level deposit and loan interest rates. For deposits, this paper focuses on 12-month fixed rate certificate of deposits (CDs), because 12-month CDs is largely standardized, which allows the comparison across branches. Also, it is the mostly reported deposit product by branches, hence minimizing the possible sample selection problem. For loans, the RateWatch database provides a less comprehensive coverage. I focus on loan products that are the most standardized and with most comprehensive coverage, including 60-month new automobile loans and personal unsecured loans.

To combine geographical information into the RateWatch data, I merge the observations on branches in the SoD with RateWatch using the branch identifier. Then, I collapse the weekly RateWatch data into branch-quarter level data following Manuszak and Wozniak (2017) by averaging each branches' observations in a given quarter. This approach smooths the variation on data and avoids the missing reporting of branches.

Panel A of Table 1 shows the summary statistics of the branch-level variables and panel B reports the the bank-level variables.

3 Impact of natural disasters on bank deposits

3.1 Effect of natural disasters on branch deposits

To investigate the impact of natural disasters on branch deposits, I estimate the following regression with branch-level deposits data from the SoD and bank-level control variables from the Call reports:

$$Deposit(ln)_{i,b,s,c,t} = \beta_0 + \beta_1 Natural\ disaster_{s,c,t} + \gamma X_{b,t-1} + \delta_{s,t} + \varepsilon_{i,b,s,c,t} \tag{1}$$

where outcome variables $Deposit(ln)_{i,b,s,c,t}$ is the logarithm of deposits of branch i of bank b located at state s and county c in year t. The variable of interest is $Natural\ disaster_{s,c,t}$, a dummy variable equals to 1 if there is any natural disaster in the county of branch i at year t. $X_{b,t-1}$ is a vector of a year-lagged bank-level control variables capturing the logarithm of assets value, interest-to-deposits ratio, tier 1 capital ratio, mortgage-to-loans ratio, net income-to-assets ratio and loan commitments-to-assets ratio[4]. The definitions of all variables are detailed in Table A.1 in the Appendix. To capture time varying state effects, such as local economic condition and business cycle, the model includes state $\times$ year fixed effects which are represented by $\delta_{s,t}$. Standard errors are clustered at county level.

Column 1-2 in Table 2 show the estimation results of equation 1. Column 1 presents the preliminary results of equation 1 without the inclusion of control variables. The coefficient of interest, β_1 in equation 1, suggests that branches exposed to natural disasters in the year experience 5.4% decrease of deposits. The estimated β_1 in column 1 is statistically significant at 1% level. The estimation results are robust to the inclusion of control variables, shown in column 2. After including a vector of control variables, the results show that natural disaster reduce branch deposits by 3.0%.

After establishing the negative impact of natural disaster on branch deposits, the next exercise verifies the conjecture that natural disasters affect branch deposits of local banks differently. To do so, I modify equation 1 by including an interaction term, $Natural\ disaster \times Local\ bank_{s,c,t}$, between the indicator variables of $Naturaldisasters$ and $Localbank$ in equation 2. The estimation model is shown as following:

$$\begin{aligned} Deposit(ln)_{i,b,s,c,t} = \beta_0 + \beta_1 Natural\ disaster_{s,c,t} + \beta_2 Local\ bank_{i,t} + \\ \beta_3 Natural\ disaster_{s,c,t} \times Local\ bank_{s,c,t} + \gamma X_{b,t-1} + \delta_{s,t} + \varepsilon_{i,b,s,c,t} \end{aligned} \tag{2}$$

where $Local\ bank_{i,t}$ is a dummy variable that equals to one if the bank is a local bank and 0, otherwise. The definitions of other variables follow equation 1. The coefficient of interest is β_3, a positive (negative) β suggests that local banks mitigate (aggravate) the adverse

[4]The selection of control variables follows Gilje et al. (2016)

effect of natural disasters on branch deposits.

Column 3 of Table 2 presents the estimation results of equation 2. The coefficient of natural disaster is consistent to the results shown in column 2. The estimated coefficient of interest, β_3, is 0.053 (t-statistics 2.03), indicating that local banks completely mitigate the adverse impact of natural disasters on deposits. Additionally, natural disasters cause 5.4% increase in deposits of local banks. The results support a redistribution of deposits among banks after natural disasters.

3.2 Dynamic effect of natural disasters on bank deposits

The annual reporting frequency of the SoD poses the challenge in identifying the short-lived dynamic impact of natural disasters on bank deposits (Cortés and Strahan, 2017). To address this issue, I use quarterly Call reports data and estimate the following model:

$$
\begin{aligned}
Deposits(ln)_{b,t} = \beta_0 &+ \beta_1 Proportion\ of\ branches\ exposed\ to\ NDs_{b,t} \\
&+\beta_2 Proportion\ of\ branches\ exposed\ to\ NDs_{b,t-1} \\
&\beta_3 Proportion\ of\ branches\ exposed\ to\ NDs_{b,t-2} \\
&+\gamma X_{b,t-1} + \delta_{s,t} + \varepsilon_{b,s,t}
\end{aligned} \tag{3}
$$

where the dependent variable $Deposits(ln)_{b,t}$ is the natural logarithm of bank deposits of bank b at year-quarter t. This set of regressions adopt a different measurement of banks' exposure to natural disasters. Considering they are bank-level regressions, the risk measurement, *Proportion of branches exposed to NDs*, is based on the proportion of branch of the bank b exposed to natural disasters. There are three coefficients of interest in this model, namely β_1, β_2 and β_3. β_1 captures the effect in the quarter of natural disasters taking place, while $\beta_{2(3)}$ captures the effect in one (two) quarter(s) after natural disasters taking place. This set of regressions is analysed by using Call reports year-quarter observations. The key advantage of the Call reports is the higher frequency of observations, allowing me to examine the dynamic effect of natural disasters on bank deposits and lending. The vector of bank control variables follow equation 1. $\delta_{s,t}$ captures headquarter state $\times$ year fixed effects and standard errors are clustered at state level.

Figure 2 reports the estimation results of equation 3. In the figure, the dot in 0 (1) (2) quarter after natural disasters shows the estimated β_1 (β_2) (β_3). The respective dash line indicates the 95% confidence interval of the estimated coefficient. The figure indicates that a percentage increased in proportion of branches exposed to the natural disasters experience 1.8% decrease in bank deposits in the quarter of natural disaster taking place and the impact lasts for another quarter following natural disasters. Consistent with previous finding on the short-lived effect of natural disasters, the impact does not last in the second quarter after natural disasters.

To shed light on the heterogeneous impact of natural disasters on local banks, I split the sample into local banks and non-local banks, then replicate the estimation above. The sub-figure on the left (right) of Figure 3 shows the estimation results for non-local banks (local banks). Consistent with the results in the previous section, the results suggest that only non-local banks' deposits are adversely affected by natural disasters and the effects last for 2 quarters after natural disasters. For local banks, natural disasters do not reduce deposits, irrespective of the periods after natural disasters.

3.3 Effect of natural disasters on branch deposits interest rates

To get a full picture of the impact of natural disasters on banks, it is important to understand the impacts on the pricing of deposits. Combined with the quantity results presented in the two previous sections, the pricing results could imply the relative changes in demand and supply of deposits after natural disasters.

To estimate the impact of natural disasters on deposit rates, I use the RateWatch data and estimate the following equation.

$$12 - month\ CD\ rate_{i,b,s,c,t} = \beta_0 + \beta_1 Natural\ disaster_{s,c,t} + \gamma X_{b,t-1} + \delta_{s,t} + \varepsilon_{i,b,t} \quad (4)$$

where the dependent variable $12 - month\ certificate\ of\ deposits\ rate_{i,b,s,c,t}$ is the interest rates of 12 months certificate of deposits of branch i of bank b located at state s and county c in year-quarter t. The definitions of all variables follow equation 1, except all variables included in this equation are in quarter frequency, and $\delta_{s,t}$ captures state x year x quarter fixed effects. Standard errors are clustered at county level. [5]

Column 1 of Table 3 reports the estimation result of the coefficient of interest, β_1, in equation 4. The results suggest that on average, banks increase 12-month CD rates by 0.025% in the quarter of natural disasters. Deposit interest rates increase while the quantity of deposits decreases after natural disasters. Hence the results imply that on average, there is a relative decrease in the supply of deposits following natural disasters.

The next column in the Table 3 presents the estimation results of equation 4 by adding the interaction term, $Natural\ disaster \times Local\ bank$, and the dummy variable $Local\ bank$. The results indicate a heterogeneous impact of natural disasters on deposit interest rates. The results show that while non-local banks increase 12-month CD rates by 0.028%, there are no statistically significant results showing local banks increase their 12-month CD rates after natural disasters. On the contrary, natural disasters reduce local banks' CD rates

[5] Equation 4 is also employed to estimate the effects of natural disaster on loan rates, the results are discussed in section 4.2.

by 0.055%, indicating that there is an increase in supply of deposits for local banks after natural disasters. The results hint at a reallocation of deposits between local and non-local banks after natural disasters.

4 Effect of natural disasters on bank lending

4.1 Effect of natural disasters on bank lending volumes

This section examines the impact of natural disasters on bank lending volumes. To implement the estimation, I study the following regression with the Call reports data:

$$
\begin{aligned}
Lending(ln)_{b,t} = \beta_0 + \beta_1 Proportion\ of\ branches\ exposed\ to\ NDs_{b,t} \\
+\gamma X_{b,t-1} + \delta_{s,t} + \varepsilon_{b,s,t}
\end{aligned}
\tag{5}
$$

where dependent variable is the natural logarithm of bank lending volumes of bank b at year-quarter t and the definition of all variables follows equation 3.

Table 4 presents the estimation results of equation 5. Column 1 shows that a percentage increase in branch exposure to natural disasters is associated with 2.1% of increase in banks' total lending, indicating that on average, banks exposed to the natural disasters increase lending to meet borrowers' need of liquidity.

Column 2 of Table 4 informs whether additional deposit inflows of local banks create additional liquidity after natural disasters. The estimated coefficient of interaction term $Naturaldisaster \times Localbank$ in column 2 suggests that local banks increase an additional 5.2% in total lending during the quarter following natural disasters. The results imply that local banks could better weather the local community through natural disasters by the additional credit supply.

4.2 Effect of natural disasters on bank loan rates

While banks on average increase lending after natural disasters, it is uncertain whether banks increase lending rates to compensate the increased credit risk. If it is the case, more deprived households may still subject to credit rationing after natural disasters.

To investigate the impact of natural disasters on bank loan rates, I employ RateWatch data of auto loans and unsecured personal loans. There are two reasons of focusing on these two categories of loan. First, RateWatch does not have comprehensive coverage of branches on different categories of loan. Auto loans and unsecured personal loans provide relatively extensive coverage, thus mitigating sample selection concern. Second, this paper avoids examining mortgages which underlying assets are directly exposed to natural disasters. Otherwise, the findings could be driven by the differences in physical damages and the risk perception of the underlying properties of mortgages.

Column 1-2 of Table 5 present the estimation results for auto loans while column 3-4 of the table present the results for personal unsecured loans. The structure of the estimation model follows equation 4, apart from the dependent variable. The dependent variable in column 1-2 is interest rates of auto loans, and the dependent variable in column 4-5 is the interest rates of personal unsecured loans. Column 1 shows no statistic evidence that natural disasters affect the interest rates of auto loans. Column 2 examines the potential heterogeneous effect on local banks and the results indicate that local banks do not adjust interest rates of auto loans differently after exposed to the natural disasters. For personal unsecured loan, the estimated coefficient in column 3 shows that natural disasters, on average, do not affect the loan rates. However, the estimation results in column 6 suggest that local banks reduce interest rates by 6.2% of personal unsecured loan after the exposure of the natural disaster.

5 Discussion-Potential channels

This paper finds that natural disasters affect banks' deposits heterogeneously: local banks receive additional supply of deposits after exposing to the natural disasters, resulting in a lower cost of deposits. Local banks also translate the additional deposit inflows and lower cost of deposits into higher credit supply. This section aims to examine four different possible channels.

5.1 Social connection

The first channel is the social connection channel which expects that depositors support local banks more due to the connection of local banks with their community.

I evaluate the social connection channel by examining whether the deposit inflows to local banks are particularly strong in counties with stronger social connection. If the additional deposit inflows are indeed caused by depositors' connection with the local banks, the additional deposit inflows of local banks should be stronger after the exposure to the natural disasters.

In validating this conjecture, I employs three measurements of social connectedness. The first one is the county-level social capital index developed by Rupasingha et al. (2006). The index takes into the consideration of numerous factors, such as voter turnovers, census response rate etc. The second measurement is the number of non-profit organization per capita. The third one is the religious adherence, capturing the proportion of population sharing the same religion.

I replicate the regression in column 3 of Table 2 (representing the bank-level deposit volumes) with the split samples by using different measurements of social connectedness. The estimation results are presented in Table 6. Column 1 (3) (5) shows the estimation results with counties which have equal to or below the non-local median of social capital index (no. of non-profit organization) (religion adherence), while Column 2 (4) (6) shows the estimation results with counties which are above the national median of social capital index (no. of non-profit organization) (religion adherence). The results are consistent across all three measurements of social connectedness. The results consistently suggest that the additional deposit inflows of local banks are particularly strong in counties with higher social connectedness. Thus, the findings are consistent to the conjecture that social connectedness is the key driver of the deposit inflows from local banks following natural disasters.

5.2 Bank soundness

An alternative explanation is the bank soundness channel which expects the additional deposit inflows are caused by the expectation that local banks are more likely to survive after natural disasters. If the inflows to local banks were simply caused by bank soundness, one would observe that banks with higher soundness, regardless of being a local or non-local banks, should receive higher deposit inflows.

To verify this channel, I employ two measurements of bank soundness, including the tier 1 capital ratio and net income to asset ratio, to split the sample. I then replicate the estimation of equation 1 based on each sub-samples. Column 1 (2) of Table 7 reports the estimation based on banks with lower than or equal to (higher than) the median value of tier 1 capital ratio, and Column 3 (4) of Table 7 reports the estimation based on banks with lower than or equal to (higher than) the median value of net income to asset ratio. Regardless of the measurements, the results consistently show no evidence that banks with higher soundness experience deposit inflows after natural disasters. Hence, the deposit inflows to local banks are unlikely to be driven by the bank soundness channel.

5.3 Government assistance

The deposit inflows to local banks could be the mechanical results of government disaster assistance if local banks systematically reside in areas with higher government disaster assistance. To verify this conjecture, I control for the total annual approved volume of U.S Small Business Administration (SBA) disaster loan on county level in the estimation of equation 2, as a proxy of government assistance after disasters.[6] The estimation results are presented in column 1 of Table 8. The results suggest that 1% increase in the SBA disaster loans indeed increase 0.4% of branch deposits. However, the inclusion of the control variable does not affect the economic magnitude and statistical significance of the variable of interest, *Disaster x Local Bank*, implying that the deposit inflows of local banks after natural disasters cannot be explained by government disaster assistance.

5.4 Local banks' market power

Presuming that natural disasters systemically happen in market with lower shares of local banks, it may explain the absence of negative effects on local banks' deposits, rather than social connectedness. If this conjecture is true, one should observe that the deposit inflows to local banks should be stronger in counties with lower market share of local banks.

To verify if that is the case, I employ two measures to proxy the market share of local banks on county level. The first one is the Herfindahl–Hirschman index (HHI) of local banks which captures the squared deposit market share of local banks across counties. The second one is the three-firm concentration index which captures the market share of the largest three local banks in counties. I then create two dummy variables, *Low HHI* and

[6]SBA disaster loans aim to assists businesses and households that experience natural disasters. Banks play limited role in originating the SBA loans, the SBA evaluates and approves loan applications, and guarantees approved loans.

Low CR3, to indicate counties with the respective measure below the 25^{th} percentile of the population. I then separately introduce the two variables into our baseline equation 2. The variables of interest are the triple interaction terms, *Disaster x Local Bank x Low HHI* and *Disaster x Local Bank x Low CR*. Positive and statistically significant coefficients of the variables support the alternative explanation.

The results are shown in column 2-3 of Table 8. The inclusion of the triple interaction terms in the regression model do not affect the baseline results. More importantly, the coefficients of both triple interaction variables are statistically insignificant at 10% level, suggesting that there is no evidence that the deposit inflows are particularly stronger in market with low local bank market share, thus market share of local bank does not seem to explain the findings.

6 Conclusion

I conclude by answering the three questions raised in the introduction of the paper. First, natural disasters, on average, reduce the supply of deposits, leading to a reduction of deposit volumes and an increase in deposit interest rates. Banks increase lending after natural disasters without adjusting interest rates of loans. Second, local banks do not experience deposit outflows after natural disasters. On the contrary, local banks experience deposit inflows, leading to an increase in deposit volumes and reduction in deposit interest rates. Following the deposit inflows, local banks increase lending. Finally, I find that the deposit inflows to local banks following natural disasters are particularly strong in counties with higher social connectedness.

The paper offers timely implications in accessing the responses of banks to natural disasters. My findings reveal that natural disasters generally do not undermine banks supply of credit, despite of the deposit outflows following natural disasters. The results highlight that natural disasters do not cause severe liquidity issue to disaster-exposed banks. However, the increasing frequency and severity of natural disasters in the coming future may change this finding.

The paper also offers an insight in evaluating the unique role of local banks in weathering local shocks. With the specialization of local market, local banks build up the relationship with the local communities and accumulate the soft information of their clients. During adverse shocks to local economies, local banks utilize these advantages to attract deposits at lower cost to increase credit supply.

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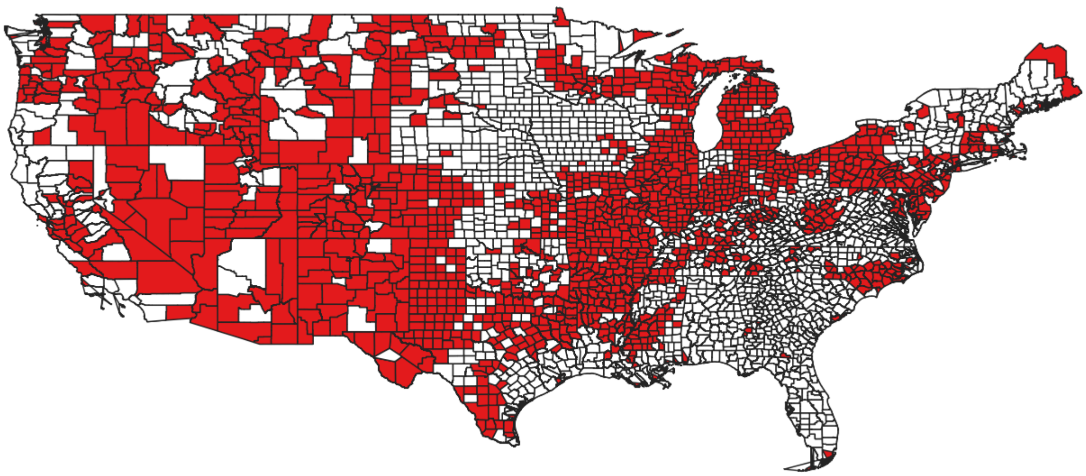
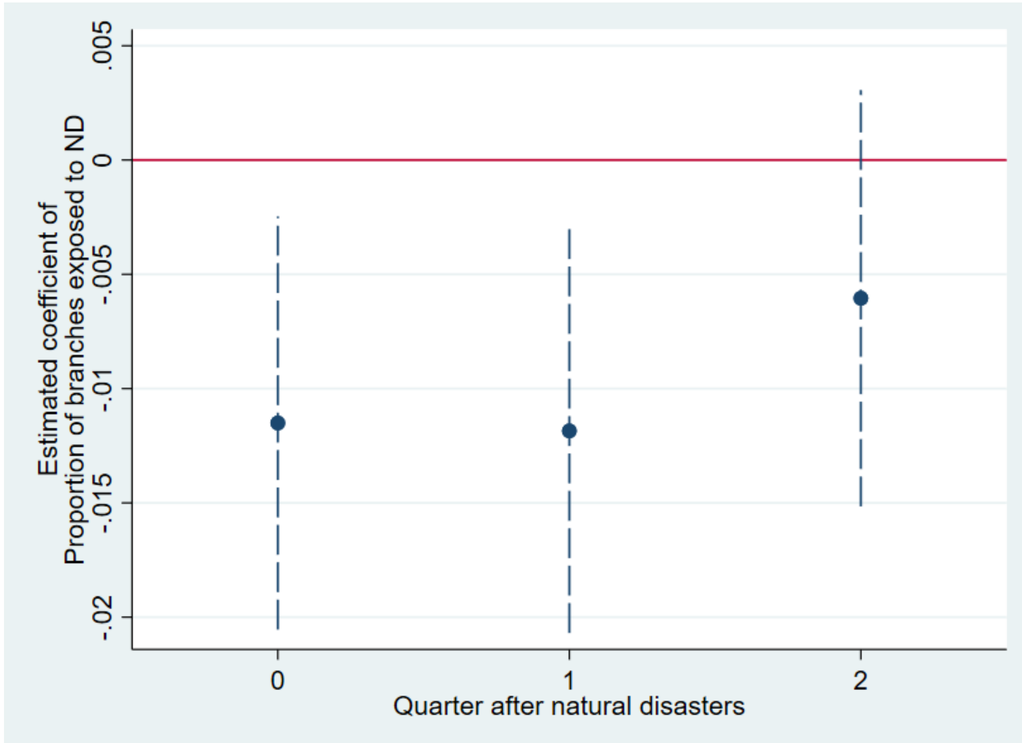
7 Tables and figures

Figure 1: Local authorities exposed to natural disasters in 2018-19



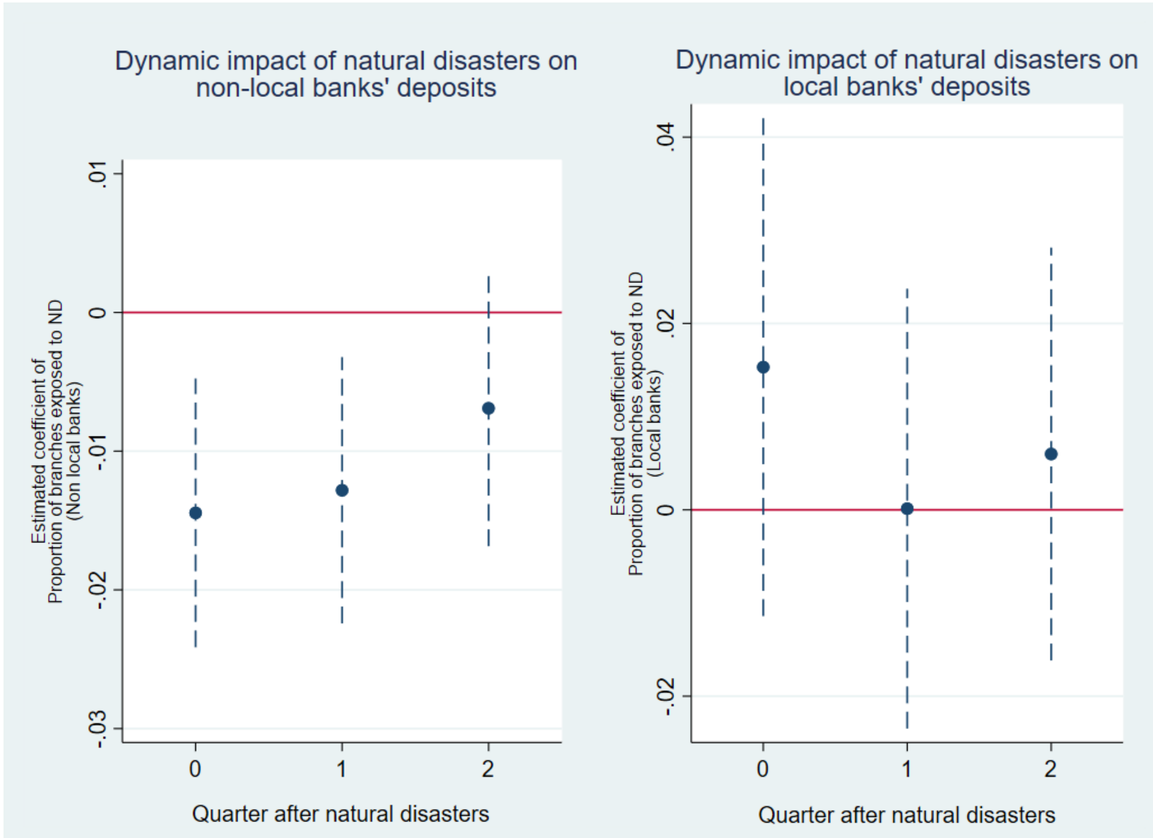
Notes: The red (white) areas of the figure indicate local authorities in the US (without) experiencing natural disasters in 2018-2019.

Figure 2: Dynamic impact of natural disasters on bank deposits



Notes: The the figure illustrates the dynamic impact of natural disasters on branch deposits, based on the equation 3. The dot at the 0 (1) (2) quarter after natural disasters represents the estimated coefficient of β_1 (β_2) (β_3) in equation 3. The dash line at the 0 (1) (2) quarter after natural disasters represents the 95% confidence interval of β_1 (β_2) (β_3) in equation 3.

Figure 3: Dynamic impact of natural disasters on bank deposits (local vs non-local bank)



Notes: The the figure illustrates the dynamic impact of natural disasters on branch deposits for non-local banks and local banks, based on the equation 3. The dot at the 0 (1) (2) quarter after natural disasters represents the estimated coefficient of β_1 (β_2) (β_3) in equation 3. The dash line at the 0 (1) (2) quarter after natural disasters represents the 95% confidence interval of β_1 (β_2) (β_3) in equation 3.

Table 1: Summary statistics

	N	Mean	SD	P5	p95
Branch-level					
Disaster	165,869	0.286	0.452	0.000	1.000
Local bank	165,869	0.066	0.247	0.000	1.000
Disaster x Local bank	165,869	0.017	0.128	0.000	0.000
Deposit volumes (ln)	168,935	10.829	0.945	8.867	12.481
12-month CD rates (%)	78,532	0.766	0.549	0.100	1.860
Auto loan rates (%)	16,725	4.949	1.131	3.290	7.000
Personal unsecured loan rates (%)	13,052	37.283	15.603	12.000	60.000
Bank-level					
Deposits (ln)	41,949	12.277	1.210	10.370	14.892
Total loans (ln)	41,949	12.019	1.310	9.840	14.771
Assets (ln)	41,949	12.502	1.456	10.547	15.160
Cost of deposits (%)	41,949	0.174	0.103	0.042	0.368
Tier 1 capital ratio (%)	41,949	11.630	4.274	8.125	18.289
Mortgage to assets ratio (%)	41,949	20.025	15.263	1.666	51.318
Net income to assets ratio (%)	41,949	0.283	1.549	-0.022	0.548
Letters of credits to assets ratio (%)	41,949	0.316	0.633	0.000	1.181

Notes: This table provides descriptive statistics for the variables used in the paper. Panel A presents branch-level variables. Panel B shows bank-level variables.

Table 2: Effect of natural disasters on branch deposits

	1	2	3
Dependent variable	Deposit volumes- branch(ln)		
Disaster	-0.053***	-0.030**	-0.033**
	(-2.76)	(-2.09)	(-2.19)
Local Bank			0.096***
			(4.20)
Disaster x Local Bank			0.053**
			(2.03)
L.Assets (ln)		0.071***	0.071***
		(27.38)	(27.96)
L.Cost of deposits		1.758***	1.716***
		(20.02)	(19.38)
L.Tier 1 capital ratio		-0.005***	-0.006***
		(-2.72)	(-3.35)
L.Mortgage to assets ratio		-0.002***	-0.003***
		(-4.24)	(-6.33)
L.Net income to assets ratio		-0.022***	-0.021***
		(-20.66)	(-20.04)
L.Letters of credits to assets ratio		0.048***	0.048***
		(15.62)	(15.69)
Observations	165,869	165,869	165,869
R-squared	0.099	0.202	0.203
State x Year FE	Yes	Yes	Yes

Notes: The dependent variable of the this table is natural logarithm of branch-level deposits. Column 1-2 of this table presents estimation results of equation 1. Column 3 of this table presents estimation results of equation 2. Definitions of variables are detailed in Table A.1 in the appendix. Standard errors are clustered at county level and the corresponding t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Effect of natural disasters on deposit interest rates

	1	2
Dependent variable	Interest rates of 12-month CDs (%)	
Disaster	0.025***	0.028***
	(2.68)	(2.91)
Local Bank		0.146***
		(2.93)
Disaster x Local Bank		-0.083*
		(-1.92)
Observations	78,532	78,532
R-squared	0.438	0.440
State x Year x Quarter FE	Yes	Yes
Bank controls	Yes	Yes

Notes: The dependent variable of the this table is interest rates of 12-month certificate of deposits (%). Column 1-2 of this table presents estimation results of equation 4. Definitions of variables are detailed in Table A.1 in the appendix. Standard errors are clustered at county level and the corresponding *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Effect of natural disasters on bank lending

	1	2
Dependent variable	Total lending (ln)	
Disaster	0.021***	0.015**
	(2.91)	(1.96)
Local Bank		-0.077***
		(-3.23)
Disaster x Local Bank		0.051**
		(2.14)
Observations	41,949	41,949
R-squared	0.891	0.891
Year x Quarter FE	Yes	Yes
Bank controls	Yes	Yes

The dependent variable of the this table is natural logarithm of bank total lending. Column 1-2 of this table presents estimation results of equation 5. Definitions of variables are detailed in Table A.1 in the appendix. Standard errors are clustered at state level and the corresponding *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Effect of natural disasters on loan rates

	1	2	3	4	5	6
Dependent variable	Interest rates (%)					
Sample	Auto New- 60 Mo Term			Personal Unsecured Loan - Max Term		
Disaster	-0.065	-0.071	-0.061	-0.345	-0.469	0.023
	(-1.33)	(-1.35)	(-1.20)	(-0.34)	(-0.42)	(0.02)
L1.Disaster		-0.105*			-0.959	
		(-1.90)			(-0.70)	
L2.Disaster		-0.012			-0.658	
		(-0.22)			(-0.55)	
Local Bank			-0.037			1.248
			(-0.26)			(0.27)
Disaster x Local Bank			-0.089			-6.203*
			(-0.50)			(-1.69)
Observations	16,725	16,725	16,725	13,052	13,052	13,052
R-squared	0.244	0.244	0.244	0.218	0.218	0.218
State x Year x Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: In column 1-3, the dependent variable of the this table is interest rates of new automobile loans (%). In column 4-6, the dependent variable of the this table is interest rates of personal unsecured loans (%). Definitions of variables are detailed in Table A.1 in the appendix. Standard errors are clustered at county level and the corresponding *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Role of social connectedness

	1	2	3	4	5	6
Dependent variable	Bank-level deposit volumes(ln)					
Sample split	Social capital index		No. of non-profit organizations		Religion adherence	
	$\leq p50$	> p50	$\leq p50$	> p50	$\leq p50$	> p50
Disaster x Local Bank	0.015	0.071**	0.005	0.069*	0.006	0.091**
	(0.37)	(2.28)	(0.12)	(1.75)	(0.14)	(2.53)
Disaster	-0.029	-0.044***	-0.028**	-0.017	-0.063**	-0.010
	(-1.25)	(-2.88)	(-2.56)	(-0.52)	(-2.45)	(-0.79)
Local Bank	0.104**	0.083***	0.073***	0.069*	0.099***	0.073***
	(2.42)	(3.63)	(3.11)	(1.94)	(3.07)	(2.63)
Observations	83,078	82,088	81,879	83,287	83,081	82,788
R-squared	0.219	0.181	0.118	0.166	0.210	0.201
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable of the this table is natural logarithm of branch-level deposits. This table presents estimation results of equation 2 based on different sub-samples. Definitions of variables are detailed in Table A.1 in the appendix. Standard errors are clustered at county level and the corresponding t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Alternative explanation: bank soundness

	1	2	3	4
Dependent variable	Branch-level deposit volumes(ln)			
Sample split	Tier 1 capital ratio (%)		Net income to assets ratio (%)	
	$\leq p50$	> p50	$\leq p50$	> p50
Disaster	-0.032	-0.017	-0.019	-0.047***
	(-1.61)	(-1.17)	(-1.01)	(-3.09)
Observations	83,590	82,273	83,028	82,839
R-squared	0.226	0.148	0.255	0.167
State x Year FE	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes

Notes: The dependent variable of the this table is natural logarithm of branch-level deposits. This table presents estimation results of equation 1 based on different sub-samples. Definitions of variables are detailed in Table A.1 in the appendix. Standard errors are clustered at county level and the corresponding t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Alternative explanation: SBA loans and market share

	1	2	3
Dependent variable	Deposit volumes- branch(ln)		
Disaster x Local Bank	0.053**	0.080**	0.061*
	(2.03)	(2.14)	(1.74)
Disaster	-0.034**	-0.052*	-0.022
	(-2.26)	(-1.70)	(-0.83)
Local bank	0.094***	0.129***	0.129***
	(4.16)	(5.13)	(5.13)
SBA loans (ln)	0.004***		
	(3.58)		
Disaster x Local Bank x Low HHI		-0.115	
		(-1.23)	
Disaster x Low HHI		0.028	
		(0.85)	
Local Bank x Low HHI		-0.201***	
		(-3.33)	
Low HHI		0.129***	
		(5.13)	
Disaster x Local Bank x Low CR3			-0.110
			(-1.09)
Disaster x Low CR3			-0.019
			(-0.65)
Local Bank x Low CR3			-0.236***
			(-3.30)
Low CR3			0.129***
			(5.13)
Observations	165,869	165,869	165,869
R-squared	0.203	0.203	0.203
State x Year FE	Yes	Yes	Yes

Notes: The dependent variable of the this table is natural logarithm of branch-level deposits. Column 1 of this table presents estimation results of equation 2 controlling total approved SBA disaster loans. Column 2-3 of this table presents estimation results of equation 2 with the respective triple interaction term. Definitions of variables are detailed in Table A.1 in the appendix. Standard errors are clustered at county level and the corresponding t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

8 Appendix

Table A.1: Variables definition

Branch-level variables	Definiton	Data source
Deposit volumes (ln)	Natural logarithm of branch-level deposits	SoD
12-month CD rates (%)	Interest rates of 12-month Certificate of Deposits	RateWatch
Auto loan rates (%)	Interest rates of new automobile loans	RateWatch
Personal unsecured loan rates (%)	Interest rates of personal unsecured loans	RateWatch
Bank-level variables		
Deposits (ln)	Natural logarithm of bank-level deposits	Call Report
Total loan (ln)	Natural logarithm of bank-level total loan	Call Report
Total assets (ln)	Natural logarithm of total assets	Call Report
Average cost of deposits	Interest expenses on deposits/total deposits	Call Report
Tier 1 capital ratio	Tier 1 capital/ total assets	Call Report
Mortgages to assets ratio (%)	Mortgage loans/ total assets	Call Report
Net income to assets ratio (%)	Net Income/total assets	Call Report
Letters of credits to assets ratio (%)	Letter of credits/total assets	Call Report
County-level variables		
Social capital index	Social capital index	Rupasingha et al. (2006)
No. of non-profit organizations per capita	No. of non-profit organizations in per capita	Rupasingha et al. (2006)
Religious adherence	Population proportion sharing the same religion	Grammich et al. (2018)
SBA loans	Total approved SBA disaster loans	U.S. Small Business Admin
HHI	Local banks' Herfindahl-Hirschman index of deposits	SoD & Author's calculation
CR3	3-firm concentration ratio of local banks	SoD & Author's calculation