Weathering the Storm: How Natural Disasters Shape Bank Consolidation

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Abstract

This paper examines the impact of natural disasters on county-level bank mergers and acquisitions (M&As) in the US from 2000 to 2019. We find that natural disasters generally lead to a decrease in M&A transactions, with acquiring banks showing increased caution towards deals involving targets based in different or distant markets. Despite this reduction in overall deal activities, banks tend to pay higher premiums for targets in these regions, potentially anticipating future performance improvements or synergies. Furthermore, heightened public awareness of climate risk appears to mitigate the negative effects of natural disasters on M&A activities, suggesting that banks may be more inclined to pursue acquisitions in areas with strong climate risk management and resilience. This study provides insights into how natural disasters influence banking behavior and M&A strategies.

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1 Introduction

The US banking system has witnessed a continuous long-term process of consolidation since the 1980s, and it is expected to undergo further reorganization in response to the recent pandemic and banking crisis. As a result, there has been a substantial reduction in the number of banks. The number of FDIC-insured commercial banks declined from 8,315 in 2000 to 4,136 in 2022, marking a 50 percent reduction. The surviving banks are typically larger, more diversified, and operate in a greater number of geographic locations (DeYoung et al., 2009). While the broad forces driving bank consolidation, such as financial and technological innovation, are widely recognized and have been extensively discussed in various review articles (e.g., Berger et al., 1999; Dymski, 2012; Amel et al., 2004; Jones and Critchfield, 2005; De Young et al., 2009), there is limited evidence regarding how natural disasters impact the bank consolidation process.

Natural disasters may influence banks' engagement in mergers and acquisitions (M&As) in several ways. First, natural disasters are frequent occurrences in countries like the US, causing substantial shocks to the local economy, including numerous fatalities and billions of dollars in property and infrastructure damage each year. Moreover, severe natural disasters result in higher out-migration rates and lower housing prices/rents (Boustan et al., 2020). Given these adversities, banks operating in disaster-affected areas may incur substantial losses after a disaster, which weakens their financial position (e.g., Hosono et al., 2016; Klomp, 2014; Do et al., 2022; Noth and Schüwer, 2023). These changes can affect banks' business perspectives and potentially motivate them to employ M&As for repositioning their geographic presence. Barth et al. (2022a) provide indirect evidence and identify a decline in the number of banks exclusively operating in a single county within areas impacted by disasters in the United States. Second, existing empirical evidence suggests that natural disasters present opportunities as well as challenges for banks. For example, credit demand increases in the wake of natural disasters as the need for funds to repair damages rises (e.g. Berg and Schrader 2012; Koetter et al., 2020; Ivanov et al., 2022). Hence, banks may choose regions based on their varying levels of exposure to disaster risks when determining where to establish their business operations (Do et al., 2022). M&As can effectively accomplish these goals.

In this study, we investigate how natural disasters shape bank consolidation in the US between 2000 and 2019. The findings indicate that natural disasters typically result in fewer M&A deals. In particular, acquiring banks tend to engage less in transactions involving targets located in different or distant markets. However, even with this decline in M&A activity, banks often pay higher premiums for targets in disaster-affected areas, possibly due to expectations of future gains or synergies. Additionally, increased public awareness of climate risks seems to lessen the adverse impact of natural disasters on M&A activities, suggesting that banks may be more willing to engage in acquisitions in regions with strong climate risk management and resilience practices.

The remainder of our paper is organized as follows: Section 2 presents the literature review and develops the research hypotheses. Section 3 describes the dataset and methodology. In Section 4, we present and discuss our results. Additional analyses are covered in Section 5. Finally, we offer concluding remarks in Section 6.

2 Literature Review and Hypotheses Development

2.1 Literature review

This study makes a broad contribution to the rapidly growing literature on climate finance and long-established banking. Some recent studies have provided insignificant or weak evidence that natural disasters affect banks. For example, Blickle et al. (2022) suggest that disasters increase loan demand, which in turn increases larger banks' profitability, while smaller local banks reduce their mortgage lending to affected areas. Garbarino and Guin (2021) find that lenders do not closely track the impact of extreme weather ex-post. Barth et al. (2022b) attribute the small impact of natural disasters on banks to the fact that affected banks simultaneously raise loan and deposit rates at branches in the affected counties, without engaging in 'profiteering'.

Nevertheless, the majority of studies have observed a consistent and significant increase in credit demand post-disaster (e.g., Berg and Schrader, 2012; Koetter et al., 2020; Ivanov et al., 2022). The picture is more mixed when it comes to the supply-side of credit. While several studies have observed significant negative effects on bank lending (e.g., Berg and Schrader, 2012; Billings et al., 2022; Nguyen and Wilson, 2020; Hosono et al., 2016; Brei et al., 2019; Duanmu et al., 2022; Javadi and Masum, 2021; Ivanov et al., 2022), others have found contradictory evidence. For example, in the US, local banks appear to expand their mortgage lending in affected counties (e.g., Duqi et al., 2021; Chavaz, 2016; Dlugosz et al., 2022; Bos et al., 2022). In Germany, local banks that operate in unaffected counties but are exposed to disaster-ridden firms in affected counties lend more in the post-flood period compared with unexposed local banks (Koetter et al., 2020). Celil et al. (2022) find that to respond to natural disasters, Chinese regional state-owned city-commercial banks (CCBs) operating within a specific city aggressively expand credit, especially to corporate borrowers. To fund additional lending, banks also increase sales of more-liquid loans or bid up their deposit rates at offices in the affected counties to attract more deposits (Barth et al., 2022b; Cortés and Strahan, 2017; Dlugosz et al., 2022). Barth et al. (2022a) further point out that the impact of natural disasters on deposit rate-setting propagates. Such spillover effects occur among branches across counties via social connections and geographical networks. Although the empirical findings differ in whether overall credit supply increases following a natural disaster, extant studies tend to agree that the presence of bank branches in affected regions mitigates some of the adverse effects on lending. Bank branches play such a role because they foster bank-borrower relationships and build local market knowledge, which ease lending restrictions and stimulate economic growth (Berg and Schrader, 2012; Billings et al., 2022; Blickle et al., 2022; Nguyen and Wilson, 2020; Koetter et al., 2020).

Other studies have generally found that natural disasters typically weaken the financial stability of banks (e.g., Klomp, 2014; Do et al., 2022; Noth and Schüwer, 2023). Moreover, Berger et al. (2022) document that banks operating in counties with higher property damages from hurricanes, tornadoes, and severe thunderstorms suffer more operational losses. Dal Maso et al. (2022) provide evidence that banks located in US counties with higher disaster risk recognize larger loan loss provisions.

A much narrower subset of climate finance literature, on the other hand, specifically investigates how climate risk impacts mergers and acquisitions. For example, Li et al. (2023) investigate how climate legislation affects the international market for corporate control. The findings reveal a notable reduction in the interest of foreign acquirers in targeting countries with climate laws in place. Dionne et al. (2023) empirically test the difference between the M&As of the life and non-life insurance sectors and find no causal link between climate risk and M&As. Bai et al. (2021), however, show that firms facing greater climate change risk from sea-level rise tend to acquire firms that are less susceptible to the direct impact of sea-level rise. Lodh et al. (2023) further discover that firms exposed to elevated climate change risk are less likely to acquire other firms and experience less shareholder value creation if they become an acquirer.

2.2 Hypotheses development

In this study, we posit that following natural disasters, banks are more likely to engage in bank M&As. This occurs along three dimensions. First, banks may encounter increased business opportunities stemming from higher deposits and loan originations post-disasters. Consequently, banks in disaster-affected regions experience improved profitability (e.g. Dlugosz et al., 2022; Cortés and Strahan, 2017; Bos et al., 2022; Barth et al., 2022a; Barth et al., 2022b). Additionally, banks can boost their profits by facilitating disaster loans on behalf of government agencies, such as the Small Business Administration (SBA). Banks are highly motivated to process SBA loans because these loans come with a government guarantee, which, from a bank's perspective, eliminates credit risk. Furthermore, banks generate non-interest income by managing SBA loans (Duqi et al., 2021). As banks become more profitable, they amass greater financial resources for acquiring other banks. Second, while banks play a crucial role in the economic recovery following disasters, like other businesses in affected areas, they also incur significant financial/operational losses (Koetter et al., 2020; Wagner, 2020; Duqi et al., 2021; Berger et al., 2022). M&As can thus serve as an effective means of risk diversification. For example, banks in regions severely impacted by natural disasters or climate risk may seek to acquire banks in geographical locations less affected by such environmental risk. Third, some studies find that natural disasters have a short-term negative effect on bank performance, as measured by their likelihood of survival (Steindl and Weinrobe, 1983, Klomp, 2014, and Noth and Schüwer, 2018). Banks that are affected are consequently more prone to acquisition, supported by evidence indicating that underperforming banks are frequently sought after for mergers (Akhigbe et al., 2004; Wheelock and Wilson, 2000; Wheelock and Wilson, 2004).

Conversely, the opposite may also be true. Natural disasters can result in diminished managerial capacity, financial stability and uncertainty regarding future losses due to banks' exposure to additional natural disasters (Hosono et al., 2016; Berger et al., 2022; Klomp, 2014; Do et al., 2022; Noth and Schüwer, 2023). Since M&As are both time-consuming and costly, affected banks may lack the desire to engage in the consolidation process or become unappealing as potential merger targets.

Given the explanations outlined above, it proves challenging to determine a priori whether natural disasters increase or reduce bank consolidation activities, and developing an answer to this question requires an empirical investigation. To account for the contradictory theoretical and empirical evidence, we, therefore, propose two alternative hypotheses:

H1A: *Natural disasters lead to an increase in bank consolidation activities.*

H1B: *Natural disasters lead to a reduction in bank consolidation activities.*

3 Data and Methodology

3.1 Data

3.1.1 Natural disasters - SHELDUS

This study employs the county-level Spatial Hazard Events and Losses Database for the United States (SHELDUS)[1], a comprehensive repository of natural disaster data. SHELDUS aggregates information from multiple authoritative sources. These include the National Climatic Data Center, the National Geophysical Data Center, and the Storm Prediction Center, which provide data on fatalities and direct economic losses associated with 18 categories of natural hazards, encompassing phenomena such as hurricanes, floods, severe storms, tornadoes, and wildfires.

Based on the recommendations from EM-DAT, we reclassify 18 groups of natural disasters into 4 groups of natural hazards as below:

- (i) hydrological disasters includes floods, and wet mass movements
- (ii) meteorological disasters entails storms, and hurricanes
- (iii) geophysical disasters includes earthquakes, tsunamis and volcanic eruption
- (iv) climatic disasters or events caused by extreme temperatures, for example, heat wave, droughts, and wildfires.

Moreover, we incorporate several key variables from SHELDUS to measure the frequency, economic damages and associated injuries and fatalities (see Appendix A for details). Table 11 presents the frequency distribution of natural disasters in the U.S. between 2000 and 2019. It is evident that certain periods were more catastrophic than others, particularly between 2008 and 2013, with a peak

[1]The SHELDUS database is maintained by the Center for Emergency Management and Homeland Security at Arizona State University (https://cemhs.asu.edu/sheldus)

in 2011. The year 2011 had the highest number of injuries and deaths resulting from natural disasters (see also Dionne et al., 2023). Overall, this granular dataset allows for a nuanced examination of the complex interplay between environmental shocks and financial sector dynamics

[Insert Table 1 here]

3.1.2 U.S banking M&A

To measure the U.S. banking consolidation process between 2000 and 2019, we extracted data on bank M&As from S&P Capital IQ Pro, which provides comprehensive deal-level information, including details on the transactions, participating firms, and other relevant metrics. We focus on market-driven transactions and exclude those deals facilitated by U.S. regulators, such as the FDIC. In total, our sample consists of 4,709 bank M&A deals in the U.S. between 2000 and 2019. Figure 1 shows the number of transactions in each year and the cyclical nature of bank consolidation in the US, with notable peaks and troughs corresponding to economic conditions such as the 2008 financial crisis. Nevertheless, the trendline indicates an overall stable and active consolidation process.

[Insert Figure 1 here]

3.1.3 Other county variables

We obtained county-level data on population, employment, and income from the Bureau of Economic Analysis website under the series Economic Profile of the County (CAINC30)[2]. Educational attainment data was sourced from the Economic Research Service of the U.S. Department of Agriculture (USDA) website[3].

To measure bank competition, we calculated the Herfindahl-Hirschman Index (HHI) for deposits on an annual basis using Summary of Deposits (SoD) data provided by the Federal Deposit Insurance Corporation (FDIC). The HHI is derived from bank deposit shares within each county, with higher values indicating more concentration and less competition.

[2]This data is available at https://apps.bea.gov/regional/downloadzip.cfm

[3]This data is available at https://www.ers.usda.gov/data-products/county-level-data-sets/county-level-data-sets-download-data/

For nonbank competition, we used the number of nonbank depository institutions and other nonbank financial institutions operating within each county. Data on these institutions were obtained from the annual County Business Patterns (CBP) series maintained by the U.S. Census Bureau.[4].

3.2 Empirical design

We begin our analysis by investigating the impact of climate-related natural disasters on the likelihood of bank mergers and acquisitions within the U.S. banking industry. To do this, we estimate probit models to assess the probability of M&A activity occurring in any given county and year as follows:

$$Prob(Deals)_{j,t} = \alpha + \beta Disasters_{j,t-1} + \gamma County_{j,t-1} + \upsilon_i + u_{j,t} + \epsilon_{j,t} \tag{1}$$

where $Deal_{j,t}$ is a variable indicating the occurrence of bank M&As. This variable is a dummy variable which is set to 1 if the aggregated number of M&A deals occurring in county j at year t is greater than zero, and 0 otherwise. Our explanatory variable of interest is $Disasters_{j,t-1}$, which is proxied by the natural logarithm count of disaster events that county j was exposed to in year $t-1$. $County_{j,t-1}$ is a set of control variables at county level, including population, employment, income, education attainment, non-bank depository institutions, non-bank financial institutions and deposit HHI.

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[4] This data is available at https://www.census.gov/programs-surveys/cbp/data/datasets.html

Appendix A provides a comprehensive list of variables used in the paper. υ_i is time fixed effect, and $u_{j,t}$ is state fixed effect while $\epsilon_{j,t}$ is an overall error term.

3.3 Summary statistics

Table 2 (Panel A) presents the summary statistics for all key variables used in our paper. The M&A dummy variable, *Deal*, has a mean of 0.0879, suggesting that deals occur in about 8.8% of the county-year observations. The summary statistics for the county-level variables reveal significant variability across important economic and demographic factors. The mean log population is 10.5, which translates to an approximate average population of 36,787 people per county when converted back to the original scale.

Similarly, the mean log total employment of 9.76 corresponds to around 17,420 jobs, and the mean log personal income of 14.0 reflects an average income of approximately $1,202. Educational attainment is consistent across counties, averaging 13.3 years. However, there is substantial disparity in the presence of non-bank financial institutions, with an average of 23.2 per county and a wide range indicating uneven access to financial services. The Herfindahl-Hirschman Index (HHI), with a mean value of 30.5 and a range from 16.9 to 100, shows that counties vary from highly competitive to more concentrated markets, potentially influencing the dynamics of mergers and acquisitions in these areas.

Table 2 (Panel B) also presents the summary statistics for the target and acquirer sample. The target and acquirer samples are constructed by combining SHELDUS data on natural disasters with information about the counties where the targets and acquirers are headquartered. Overall, the comparison between the target and acquirer samples reveals that both operate in very similar environments, with only minor differences worth noting.

The target sample demonstrates a slightly higher likelihood of deals occurring, as indicated by the M&A Deal dummy variable. This increased likelihood is attributed to the fact that acquirers, who tend to survive longer, are more likely to be involved in multiple M&A transactions. Consequently, their engagement in M&As is more prevalent compared to targets. The acquirer sample, on the other hand, shows marginally higher total and property damages from disasters. Nevertheless, the differences between two subsamples are generally small, indicating that both target and acquirer counties have comparable exposure to disasters and similar economic conditions.

[Insert Table 2 here]

4 Empirical Results

4.1 Baseline results

In Table 3, we show the impact of natural disasters on the probability of at least one bank M&A taking place in a US county, using the probit model detailed in Equation (1). The results are divided into three samples: full sample, acquirers and targets. The table reports the average marginal effects for each variable. Column 1 shows that natural disasters have a negative and significant association with the likelihood that a bank M&A occurs.

The marginal effect is equal to -0.0111 and statistically significant at the 0.1% level. This result suggests that a higher frequency of natural disasters surrounding bank headquarters is associated with a lower probability that a bank engages in M&A. The economic effect is sizeable: a one-standard deviation increase in the county-level measure of total natural disasters is associated with a statistically significant 1% (-0.0111×0.9015) lower probability of observing at least one bank M&A deal. Relative to the average probability of 8.8%, this corresponds to a decrease in the probability of M&A occurrence of approximately 11% ($-0.0100/0.0879$).

In Column 2, we test the impact using the acquirer sample. The size of the marginal effect for natural disasters decreases but remains negative and statistically significant at the 5% level. The results from the target sample in Column 3 show that the marginal effect (i.e. -0.0103) is larger and more significant (i.e. 0.1%) than that for the acquirer sample, suggesting that our full sample results are, to some extent, more driven by targets. Our baseline results suggest that our hypothesis H1B holds: natural disasters lead to a reduction in bank consolidation activities.

[Insert Table 3 here]

4.2 Alternative measures for natural disasters

Having established a baseline understanding of the impact of natural disasters on the bank consolidation process, we further examine this relationship using alternative measures of natural disasters. First, we divide our natural disaster measure into four categories, namely hydrological disasters, meteorological disasters, geophysical disasters, and climatic disasters. We then test how each category of natural disasters affects banks' merger decisions using the probit model.

Table 4 presents the results from three different samples. Overall, meteorological disasters have the most significant and largest marginal effects compared to the other three categories of natural disasters, while climatic disasters have the second most significant effects. Moreover, we find consistent patterns showing that different types of natural disasters tend to negatively affect a bank's likelihood of becoming a merger target more than they affect acquiring banks

[Insert Table 4 here]

Second, we use severity-based measures to assess how natural disasters influence M&A activities. These measures include total damages, which encompasses two sub-measures: crop damages and property damages, as well as injuries and fatalities. We run the probit model using these five measures as independent variables and show our results in Table 5. We find that total damages, as well as one of its sub-measures—property damages—tend to negatively impact bank mergers, particularly the likelihood of a bank becoming a target.

[Insert Table 5 here]

5 Extra analyses

5.1 Deal characteristics

To explore more nuanced probabilities of a target bank being acquired while based in an area affected by natural disasters, we conduct additional tests to examine the strategic preferences and risk considerations of acquiring banks in various scenarios. First, we collect deal information from S&P Capital IQ Pro and divide our bank M&A sample into two subsets. The first subset comprises market expansion transactions, where the target bank shares no common markets with the buyer. The second subset involves in-market transactions, where the target and buyer's branch networks fully or partially overlap. Subsequently, we conduct probit regressions on these subsets to assess the likelihood of at least one bank being acquired in an M&A deal while headquartered in a disaster-affected area and engaged in a specific type of transaction—namely, market expansion or in-market, respectively.

Table 6, Panels A and B, shows results involving market expansion deals and in-market transactions, in turn. Both subsets show consistent and similar results with the baseline. There are significant differences observed, nevertheless, that acquiring banks are less likely to expand their markets into disaster-affected areas. For example, the marginal effect of a market expansion deal occurring, when the total number of natural disasters is considered, is -0.0066 and statistically significant at the 0.1% level, which is greater and more significant than that for an in-market deal. The results suggest that acquiring banks are generally more risk-averse in disaster-affected areas, particularly when expanding into new markets.

[Insert Table 6 here]

Second, we consider the geographical distance between the acquiring and target banks to gain insights into the impact of natural disasters on acquisition decisions. To do this, we split our M&A sample into two sub-samples based on the distance between the headquarters of the acquiring bank and the target bank. The first sub-sample encompasses deals where the distance exceeds 100 miles, while the second sub-sample includes transactions taking place within a 100-mile radius. We measure the distance between the counties where the acquiring bank and its target are headquartered using the county distance database provided by the National Bureau of Economic Research (NBER).

We then re-estimate our probit regressions on target banks using these sub-samples. Table 7, Panels A and B, report that for longer-distance transactions, the presence of disasters, particularly meteorological ones, significantly reduces the likelihood of M&A deals. Acquiring banks appear to be more cautious about taking over targets in disaster-hit regions, especially at greater distances.

[Insert Table 7 here]

Next, building on the existing literature on the determinants of merger premiums, we examine whether natural disasters are a factor when acquiring banks evaluate their targets. We first calculate *premium_bv*, which is the purchase price paid by the acquiring institution scaled by the pre-merger book value of the target bank's equity. The independent variable of interest is the total number of natural disasters in natural logarithm in the target's county. We also include a list of well-acknowledged determinants of banking merger premiums that control whether the deals are focusing or diversifying, the relative performance of targets compared to acquiring banks and means of payment.

Table 8 presents the results from our OLS regressions and shows interesting findings: within our sample period, acquiring banks tend to pay more to purchase a target based in a disaster-affected county. These findings are somewhat unexpected, as our results thus far suggest that acquiring banks generally avoid targets with a higher risk of experiencing natural disasters. One possible explanation is that banks might see enhanced profitability following disasters. This is due to the increased business opportunities resulting from higher deposits and loan origination activities in areas affected by disasters (e.g. Dlugosz et al., 2022; Cort'es and Strahan, 2017; Bos et al., 2022; Barth et al., 2022a; Barth et al., 2022b). A further empirical examination, therefore, is warranted.

[Insert Table 8 here]

To investigate the effects of natural disasters on banking consolidation and post-merger performance,we employ a difference-in-differences (DiD) analysis centered around M&A announcement dates. Our methodology involves constructing event windows and executing a series of regressions to examine how natural disasters influence various financial metrics of the banks involved, while controlling for year and firm fixed effects. Our DiD regressions focus on key bank performance indicators such as return on assets (ROA), return on equity (ROE), leverage ratios, and Tier 1 and Tier 2 capital ratios extracted from Compustat. We examine these metrics in the year preceding the merger announcement ($t-1$), the announcement year (t), and the year following the announcement ($t+1$). This temporal analysis allows us to capture both immediate and short-term effects of the mergers. The treatment group in our analysis consists of target banks located in areas with higher exposure to natural disasters compared to their acquiring banks. This design enables us to isolate the impact of differential disaster exposure on post-merger synergies and financial performance.

Table 9 indicates that these 'treated' banks tend to show improved profitability post-merger, as evidenced by positive and significant coefficients for ROA and ROE. Specifically, the coefficients for ROA are all positive and significant at the 1% level, while the coefficients for ROE range from 0.0034 to 0.0038 and are significant at the 1% and 5% levels. This suggests that banks engaging in M&A activities in disaster-prone areas may be able to achieve synergies that enhance their profitability.

The effects on capital ratios, however, present a mixed picture. Tier 1 capital shows no significant immediate effect post-merger, but there is some evidence of improvement in later periods, whereas Tier 2 capital shows a slight positive effect post-merger. Leverage ratios, on the other hand, tend to decrease post-merger for these banks. This decrease in leverage suggests improved financial stability, which is particularly noteworthy given the higher risk environment these banks operate in.

While our results confirm that M&A activities in areas more exposed to natural disasters may lead to improved bank performance and resilience, it is important to note that these findings should be interpreted cautiously, as the specific mechanisms driving the improvement, and their long-term sustainability warrant further investigation.

[Insert Table 9 here]

5.2 Media attention: Climate survey

With increasing awareness about climate change and global warming, we incorporate data from the Yale Climate Opinion Maps (YCOM)[5] into our investigation on the impact of natural disasters on bank mergers and acquisitions. According to recent surveys, a growing majority of people globally, especially in Europe, view climate change as one of the greatest threats to their countries. A 2022 Pew Research Center survey found that a median of 75% of people across 19 countries see climate change as a major threat. Similarly, the Yale Program on Climate Change Communication has found that 72% of Americans think global warming is happening, and 57% are worried about it.

The YCOM data provides granular insights into public opinion on these issues at the county level across the United States. This dataset includes variables such as the perceived risk of global warming, belief in the occurrence of climate change, and support for climate policies. Utilizing YCOM data in our regression analysis allows us to account for the local population's awareness and concern about climate change. By interacting this data with natural disaster occurrences, we can more accurately capture how public opinion on climate risks may influence banks' decisions related to mergers and acquisitions. Specifically, banks may be more or less likely to engage in such transactions in counties where the population is more cognizant and concerned about climate change and its associated risks. This interaction helps in understanding the broader impacts of natural disasters on economic activities beyond immediate physical damages, reflecting wider societal and behavioural responses.

In our analysis of YCOM data, we focus on two key variables: (1) *Happening*, which represents the estimated percentage of people who believe global warming is occurring, and (2) *Timing*, which

[5]This data is available at https://climatecommunication.yale.edu/visualizations-data/ycom-us/

reflects the estimated percentage of people who believe global warming will begin to harm people in the U.S. either now or within the next 10 years. Data for these variables is available from 2014 to 2023, except for gaps in 2015 and 2017. To address these missing years, we imputed the values by averaging the data from the preceding and following years. We then create a dummy variable, *high_happening*, which equals 1 if the percentage of people who believe in global warming exceeds the median value, and 0 otherwise. Similarly, *high_timing* is a dummy variable set to 1 if the percentage of people who think global warming will harm people within 10 years is above the median, and 0 otherwise.

These dummy variables are then interacted with the measurement of natural disasters in a county when we rerun the probit regressions for our acquirer and target samples. The results are presented in Table 10. The interaction terms in the regression results reveal how public perceptions about global warming moderate the relationship between natural disasters and the likelihood of a deal. Specifically, the interaction between *high_timing* and *log_record* shows a positive and significant coefficient (e.g., in column (1) for the target sample and column (5) for the acquirer sample), indicating that when a higher percentage of people believe that global warming will harm people within the next 10 years, the typically negative impact of natural disasters on deal likelihood is lessened.

Similarly, the interaction between *high_happening* and *log_record* also presents a positive (in both samples) and significant effect (only for the target sample, as seen in columns (3) and (7)), suggesting that in regions where people are more conscious of or responsive to the risks of climate change, the occurrence of a natural disaster may not discourage corporate deals as strongly, possibly because these regions are better prepared for or more accepting of the associated risks.

[Insert Table 10 here]

6 Conclusion and Remark

This paper explores how natural disasters influence county-level M&A activities in the US between 2000 and 2019. Our findings reveal that natural disasters lead to a reduction in M&A deals, with acquiring banks being particularly cautious about expanding into disaster-hit areas or engaging in acquisitions involving targets in distant markets. This suggests that banks are wary of entering new markets or taking on additional risks when natural disasters are a factor.

Further analysis indicates that, despite this reduction in deal activity, acquiring banks tend to pay higher premiums for targets located in disaster-affected areas. This could be driven by the potential for performance improvement post-merger, as banks may anticipate greater returns or synergies from these acquisitions. Additionally, our study finds that public opinion related to climate risk can also mitigate the negative impact of natural disasters on bank consolidation. This suggests that in counties where there is heightened awareness and concern about climate change, banks may be more willing to engage in M&As, recognizing the community's proactive stance on risk management and resilience.

In contributing to the literature on natural disasters and banking behavior, this study offers valuable insights for policy considerations. Regulators can leverage these findings to gain a deeper grasp of how natural disasters influence banks' consolidation strategies, particularly in terms of their risk assessment and market expansion decisions. By recognizing the patterns and impacts observed in this study, regulators may be better equipped to monitor and scrutinize banks that are less active or excluded from consolidation activities in disaster-prone areas. This can also help ensure that banking regulators' approval of M&A deals is more informed by a thorough analysis of environmental risks.

Moreover, this study highlights the importance of incorporating public opinion and climate awareness into regulatory frameworks. Regulators can use these insights to refine their oversight strategies, placing additional focus on banks that may be more vulnerable to or affected by natural disaster risks. Policymakers, in turn, can explore initiatives to bolster community resilience and climate risk awareness, which could foster a more robust and adaptable banking system. Ultimately, this research emphasizes the need for a nuanced view of the interplay between natural disasters, public sentiment, and financial decision-making. By integrating these factors into regulatory and policy frameworks, the banking sector can be better prepared to handle the challenges posed by environmental risks, thereby enhancing the stability and resilience of the financial system.

References

Akhigbe, A., Madura, J., & Whyte, A. M. (2004). Partial anticipation and the gains to bank merger targets. *Journal of Financial Services Research*, *26*, 55–71.

Bai, J. J., Chu, Y., Shen, C., & Wan, C. (2021). *Managing climate change risks: Sea level rise and mergers and acquisitions* [Available at SSRN: https://ssrn.com/abstract=3739599].

Barth, J. R., Hu, Q., Sickles, R. C., Sun, Y., & Yu, F. (2022). *Spillover effects of natural disasters on banks: A spatial framework* [Available at SSRN 4118057].

Barth, J. R., Miller, S. M., Sun, Y., & Zhang, S. (2022). Natural disaster impacts on us banks. *American Business Review*, *25*(2), 10.

Berg, G., & Schrader, J. (2012). Access to credit, natural disasters, and relationship lending. *Journal of Financial Intermediation*, *21*(4), 549–568.

Berger, A. N., Curti, F., Lazaryan, N., Mihov, A., & Roman, R. A. (2022). *Climate risks in the us banking sector: Evidence from operational losses and extreme storms* [Available at SSRN 4294026].

Billings, M. B., Ryan, S. G., & Yan, H. (2022). *Climate risk, population migration, and banks' lending and deposit-taking activities* [Population Migration, and Banks' Lending and Deposit-Taking Activities (October 10, 2022)].

Blickle, K., Hamerling, S. N., & Morgan, D. P. (2021). *How bad are weather disasters for banks?* (Staff Report No. 990). FRB of New York.

Bos, J. W., Li, R., & Sanders, M. W. (2022). Hazardous lending: The impact of natural disasters on bank asset portfolio. *Economic Modelling*, *108*, 105760.

Brei, M., Mohan, P., & Strobl, E. (2019). The impact of natural disasters on the banking sector: Evidence from hurricane strikes in the caribbean. *The Quarterly Review of Economics and Finance*, *72*, 232–239.

Celil, H. S., Oh, S., & Selvam, S. (2022). Natural disasters and the role of regional lenders in economic recovery. *Journal of Empirical Finance*, *68*, 116–132.

Chavaz, M. (2016). *Dis-integrating credit markets: Diversification, securitization, and lending in a recovery* (Staff Working Paper No. 61). Bank of England.

Cortés, K. R., & Strahan, P. E. (2017). Tracing out capital flows: How financially integrated banks respond to natural disasters. *Journal of Financial Economics*, *125*(1), 182–199.

Dal Maso, L., Kanagaretnam, K., Lobo, G. J., & Mazzi, F. (2022). Does disaster risk relate to banks' loan loss provisions? *European Accounting Review*, 1–30.

Dionne, G., Fenou, A., & Mnasri, M. (2023). *Consolidation of the us property and casualty insurance industry: Is climate risk a causal factor for mergers and acquisitions?* [Available at SSRN 4364952].

Dlugosz, J., Gam, Y. K., Gopalan, R., & Skrastins, J. (2022). *Decision-making delegation in banks* [Available at SSRN 3155683].

Do, Q. A., Phan, V., & Nguyen, D. T. (2022). How do local banks respond to natural disasters? *The European Journal of Finance*, *29*(7), 1–26.

Duanmu, J., Li, Y., Lin, M., & Tahsin, S. (2022). Natural disaster risk and residential mortgage lending standards. *Journal of Real Estate Research*, *44*(1), 106–130.

Duqi, A., McGowan, D., Onali, E., & Torluccio, G. (2021). Natural disasters and economic growth: The role of banking market structure. *Journal of Corporate Finance*, *71*, 102101.

EM-DAT. (2019). Ofda/cred international disaster database [[Accessed 24.06.2021]].

Garbarino, N., & Guin, B. (2021). High water, no marks? biased lending after extreme weather. *Journal of Financial Stability*, *54*, 100874.

Hosono, K., Miyakawa, D., Uchino, T., Hazama, M., Ono, A., Uchida, H., & Uesugi, I. (2016). Natural disasters, damage to banks, and firm investment. *International Economic Review*, *57*(4), 1335–1370.

Ivanov, I. T., Macchiavelli, M., & Santos, J. A. (2022). Bank lending networks and the propagation of natural disasters. *Financial Management*, *51*(3), 903–927.

Javadi, S., & Masum, A. A. (2021). The impact of climate change on the cost of bank loans. *Journal of Corporate Finance*, *69*, 102019.

Klomp, J. (2014). Financial fragility and natural disasters: An empirical analysis. *Journal of Financial Stability*, *13*, 180–192.

Koetter, M., Noth, F., & Rehbein, O. (2020). Borrowers under water! rare disasters, regional banks, and recovery lending. *Journal of Financial Intermediation*, *43*, 100811.

Li, T., Tang, D. Y., & Xie, F. (2023). *Climate laws and cross-border mergers and acquisitions* [Working Paper, University of Hong Kong].

Lodh, S., Deshmukh, N., & Rohani, A. (2023). Stemming the tide: Does climate risk affect m&a success? *Business Strategy and the Environment*, 1–24.

Nguyen, L., & Wilson, J. O. (2020). How does credit supply react to a natural disaster? evidence from the indian ocean tsunami. *The European Journal of Finance*, *26*(7-8), 802–819.

Noth, F., & Schüwer, U. (2023). Natural disasters and bank stability: Evidence from the us financial system. *Journal of Environmental Economics and Management*, *119*, 102792.

Steindl, F. G., & Weinrobe, M. D. (1983). Natural hazards and deposit behavior at financial institutions: A note. *Journal of Banking and Finance*, *7*(1), 111–118.

Wagner, K. R. (2022). Adaptation and adverse selection in markets for natural disaster insurance. *American Economic Journal: Economic Policy*, *14*(3), 380–421.

Wheelock, D. C., & Wilson, P. W. (2004). Consolidation in us banking: Which banks engage in mergers? *Review of Financial Economics*, *13*(1-2), 7–39.

Wheelock, D. C., & Wilson, P. W. (2000). Why do banks disappear? the determinants of us bank failures and acquisitions. *Review of Economics and Statistics*, *82*(1), 127–138.

Table 1: Frequency distribution of natural disasters in the U.S. between 2000 and 2019

Year	All disasters (total)	Hydrological disasters	Meteorological disasters	Geophysical disasters	Climatic disasters
2000	20666	1590	17073	2	2001
2001	17782	2002	14841	14	925
2002	18407	1581	15608	6	1212
2003	19646	2457	15884	1	1304
2004	18307	2277	15083	4	943
2005	18597	2373	14505	3	1716
2006	21025	1644	18020	16	1345
2007	21288	2579	16272	1	2436
2008	30521	3403	25369	8	1741
2009	23981	2921	19711	5	1344
2010	27350	3265	22462	6	1617
2011	35810	3091	30217	20	2482
2012	26459	1781	22978	11	1689
2013	23518	3091	18581	1	1845
2014	21969	2501	17849	7	1612
2015	20867	3228	16412	4	1223
2016	19518	2188	16538	3	789
2017	21611	2179	18589	0	843
2018	18711	2672	15149	4	886
2019	22377	2903	18787	6	681

Notes:

Table 2: Descriptive statistics

	Mean	SD	Q1	Median	Q3	Min	Max
M&A Deal dummy	0.0879	0.2831	0.0000	0.0000	0.0000	0.0000	1.0000
Log (1+ Number of All disasters)	1.8674	0.9015	1.0986	1.7918	2.4849	0.0000	5.5094
Log (1+ Number of Hydrological disasters)	0.4316	0.6113	0.0000	0.0000	0.6931	0.0000	4.2195
Log (1+ Number of Meterogological disasters)	1.6344	0.9869	1.0986	1.6094	2.3979	0.0000	5.2417
Log (1+ Number of Geophysical disasters)	0.0015	0.0352	0.0000	0.0000	0.0000	0.0000	1.3863
Log (1+ Number of Climatic disasters)	0.2471	0.5052	0.0000	0.0000	0.0000	0.0000	3.8067
Number of All disasters	8.7929	10.7280	2.0000	5.0000	11.0000	0.0000	246.0000
Number of Hydrological disasters	0.9751	2.2041	0.0000	0.0000	1.0000	0.0000	67.0000
Number of Meterogological disasters	7.2539	9.5046	2.0000	4.0000	10.0000	0.0000	188.0000
Number of Geophysical disasters	0.0024	0.0577	0.0000	0.0000	0.0000	0.0000	3.0000
Number of Climatic disasters	0.5615	1.7616	0.0000	0.0000	0.0000	0.0000	44.0000
Crop damages	2.1394	4.7316	0.0000	0.0000	0.0000	0.0000	21.1520
Property damages	10.7770	3.8660	9.4046	11.3050	13.0710	0.0000	23.7900
Total damages	11.0500	3.8614	9.6159	11.5130	13.3120	0.0000	23.7900
Injuries	0.1984	0.5798	0.0000	0.0000	0.0000	0.0000	7.0493
Fatalities	0.0909	0.3132	0.0000	0.0000	0.0000	0.0000	6.4599
Population	10.4640	1.4530	9.5150	10.3410	11.3240	4.0073	16.1300
Total Employment	9.7617	1.5196	8.6793	9.5962	10.6710	4.0073	15.7000
Personal income	13.9600	1.5625	12.8940	13.7680	14.8580	8.0586	20.4070
Education attainment	13.2560	0.9141	12.6340	13.2440	13.8530	8.9709	16.9770
Nonbank_depository_institutions	7.7847	17.5400	1.0000	2.0000	7.0000	0.0000	313.0000
Nonbank_financial_institutions	23.1510	71.2580	2.0000	6.0000	17.0000	0.0000	2077.0000
HHI	30.5370	20.0540	16.8570	24.6890	37.3370	4.6636	100.0000

Variable	Panel A: Target sample			Panel B: Acquirer sample			$\Delta Mean$
	Obs	Mean	Std. dev.	Obs	Mean	Std. dev.	
M&A Deal dummy	50,322	0.0857	0.2799	50,198	0.0734	0.2607	0.0123
Log (1+ Number of All disasters)	50,322	1.8924	0.8810	50,198	1.8971	0.8771	-0.0047
Log (1+ Number of Hydrological disasters)	50,322	0.9882	2.2159	50,198	0.9906	2.2181	-0.0024
Log (1+ Number of Meterogological disasters)	50,322	7.3512	9.5307	50,198	7.3694	9.5354	-0.0182
Log (1+ Number of Geophysical disasters)	50,322	0.0024	0.0581	50,198	0.0024	0.0581	0.0000
Log (1+ Number of Climatic disasters)	50,322	0.5690	1.7722	50,198	0.5704	1.7742	-0.0014
Number of All disasters	50,322	8.9108	10.7505	50,198	8.9328	10.7546	-0.0220
Number of Hydrological disasters	50,322	0.9882	2.2159	50,198	0.9906	2.2181	-0.0024
Number of Meterogological disasters	50,322	7.3512	9.5307	50,198	7.3694	9.5354	-0.0182
Number of Geophysical disasters	50,322	0.0024	0.0581	50,198	0.0024	0.0581	0.0000
Number of Climatic disasters	50,322	0.5690	1.7722	50,198	0.5704	1.7742	-0.0014
Crop damages	50,322	2.1681	4.7567	50,198	2.1735	4.7613	-0.0054
Property damages	50,322	10.9211	3.6834	50,198	10.9481	3.6477	-0.0270
Total damages	50,322	11.1982	3.6675	50,198	11.2259	3.6295	-0.0277
Injuries	50,322	0.2011	0.5832	50,198	0.2016	0.5839	-0.0005
Fatalities	50,322	0.0921	0.3151	50,198	0.0923	0.3154	-0.0002
Population	48,322	10.4570	1.4498	48,183	10.4605	1.4492	-0.0036
Total Employment	48,322	9.7528	1.5157	48,183	9.7571	1.5157	-0.0043
Personal income	48,322	13.9502	1.5578	48,183	13.9539	1.5574	-0.0037
Education attainment	50,138	13.2494	0.9127	49,995	13.2502	0.9129	-0.0008
Nonbank_depository_institutions	40,838	7.7373	17.4673	40,753	7.7581	17.5097	-0.0208
Nonbank_financial_institutions	40,838	23.0217	70.9532	40,753	23.0791	71.2778	-0.0573
HHI	32,671	30.5565	20.0768	32,623	30.5512	20.0530	0.0053

Notes: This table illustrates the descriptive statistics for our variables.

Table 3: The impact of natural disaster on banks' M&A

	(1)	(2)	(3)
Dependent variable		P(Deal=1)	
Sample:	Full sample	Acquirer sample	Target sample
	Margin	Margin	Margin
L.Log (1+ Number of disasters)	-0.0111***	-0.0058*	-0.0103***
	(0.0024)	(0.0024)	(0.0023)
L.Population	-0.0818***	-0.0776***	-0.0381**
	(0.0174)	(0.0174)	(0.0135)
L.Employment	0.1081***	0.1074***	0.0278**
	(0.0127)	(0.0127)	(0.0096)
L.Personal income	0.0161	0.0134	0.0457***
	(0.0158)	(0.0159)	(0.0131)
L.Deposit HHI	-0.0071	-0.0083+	-0.0082*
	(0.0051)	(0.0050)	(0.0040)
L.Education attainment	-0.0001	-0.0001	0.0002
	(0.0002)	(0.0002)	(0.0002)
L.Nonbank depository institutions	0.0001*	0.0001*	0.0001**
	(0.0000)	(0.0000)	(0.0001)
L.Nonbank financial institutions	0.0008***	0.0008***	-0.0006**
	(0.0002)	(0.0002)	(0.0002)
Time FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Cluster of S.E.	County	County	County
Observations	23514	23248	23278
R-squared	0.1897	0.2009	0.1693

Notes: This table presents our baseline results. Robust standard errors are reported in parentheses: +p $<$ 0.1, *p $<$ 0.05, **p $<$ 0.01, ***p $<$ 0.001

Table 4: Alternative measures for natural disasters (1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable	P(Deal=1)											
	Panel A: Full sample				Panel B: Acquirer sample				Panel C: Target sample			
	Margin	Margin	Margin	Margin	Margin	Margin	Margin	Margin	Margin	Margin	Margin	Margin
Log (1+ Number of Hydrological disasters)	-0.0016				0.0010				-0.0029			
	(0.0028)				(0.0027)				(0.0026)			
Log (1+ Number of Meteorological disasters)		-0.0083***				-0.0041+				-0.0077***		
		(0.0022)				(0.0022)				(0.0021)		
Log (1+ Number of Geophysical disasters)			-0.0039				0.0053				-0.0236	
			(0.0364)				(0.0344)				(0.0479)	
Log (1+ Number of Climatic disasters)				-0.0072+				-0.0040				-0.0086**
				(0.0037)				(0.0035)				(0.0031)
Controls (Table 3)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster of S.E.	County	County	County	County	County	County	County	County	County	County	County	County
Observation	23514	23514	23514	23514	23248	23248	23248	23248	23278	23278	23278	23278
R-squared	0.1875	0.1889	0.1875	0.1879	0.2002	0.2006	0.2002	0.2004	0.1676	0.1687	0.1675	0.1680

Notes: Robust standard errors are reported in parentheses: +p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001

Table 5: Alternative measures for natural disasters (2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Dependent variable								P(Deal=1)							
	Panel A: Full sample					Panel B: Acquirer sample					Panel C: Target sample				
	Margin	Margin	Margin	Margin	Margin	Margin	Margin	Margin	Margin	Margin	Margin	Margin	Margin	Margin	Margin
Crop damages	-0.0003					0.0001					-0.0007+				
	(0.0004)					(0.0004)					(0.0004)				
Property damages		-0.0020***					-0.0010*					-0.0013*			
		(0.0005)					(0.0005)					(0.0005)			
Total damages			-0.0020***					-0.0010+					-0.0015**		
			(0.0005)					(0.0005)					(0.0005)		
Injuries				0.0052*					0.0043+					0.0033	
				(0.0023)					(0.0022)					(0.0025)	
Fatalities					0.0008					-0.0003					-0.0025
					(0.0047)					(0.0045)					(0.0044)
Controls (Table 3)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster of S.E.	County	County	County	County	County	County	County	County	County	County	County	County	County	County	County
Observation	23514	23514	23514	23514	23514	23248	23248	23248	23248	23248	23278	23278	23278	23278	23278
R-squared	0.1875	0.1888	0.1888	0.1878	0.1875	0.2002	0.2006	0.2005	0.2005	0.2002	0.1678	0.1680	0.1681	0.1677	0.1675

Notes: Robust standard errors are reported in parentheses: +p $<$ 0.1, *p $<$ 0.05, **p $<$ 0.01, ***p $<$ 0.001

Table 6: Deal characteristics: Market expansion and In-market samples

	(1)	(2)	(3)	(4)	(5)
Panel A: Market expansion sample					
Dependent variable	P(Deal=1)				
	Margin	Margin	Margin	Margin	Margin
L.Log (1+ Number of disasters)	-0.0066***				
	(0.0015)				
L.Log (1+ Number of Hydrological disasters)		-0.0028			
		(0.0018)			
L.Log (1+ Number of Meteorological disasters)			-0.0050***		
			(0.0013)		
L.Log (1+ Number of Geophysical disasters)				0.0037	
				(0.0305)	
L.Log (1+ Number of Climatic disasters)					-0.0048*
					(0.0020)
Controls (Table 3)	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Cluster of S.E.	County	County	County	County	County
Observation	33306	33306	33306	33306	33306
R-squared	0.1251	0.1234	0.1244	0.1232	0.1236
	(1)	(2)	(3)	(4)	(5)
Panel B: In-market sample					
Dependent variable	P(Deal=1)				
	Margin	Margin	Margin	Margin	Margin
L.Log (1+ Number of disasters)	-0.0040**				
	(0.0014)				
L.Log (1+ Number of Hydrological disasters)		-0.0019			
		(0.0017)			
L.Log (1+ Number of Meteorological disasters)			-0.0032*		
			(0.0013)		
L.Log (1+ Number of Geophysical disasters)				0.0098	
				(0.0281)	
L.Log (1+ Number of Climatic disasters)					-0.0012
					(0.0019)
Controls (Table 3)	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Cluster of S.E.	County	County	County	County	County
Observation	33073	33073	33073	33073	33073
R-squared	0.2165	0.2158	0.2163	0.2157	0.2158

Notes: Robust standard errors are reported in parentheses: +p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001

Table 7: Deal proximity: Below and above 100 miles samples

	(1)	(2)	(3)	(4)	(5)
Panel A: Above 100 miles sample					
Dependent variable			P(Deal=1)		
	Margin	Margin	Margin	Margin	Margin
L.Log (1+ Number of disasters)	-0.0064***				
	(0.0015)				
L.Log (1+ Number of Hydrological disasters)		-0.0035*			
		(0.0018)			
L.Log (1+ Number of Meteorological disasters)			-0.0050***		
			(0.0014)		
L.Log (1+ Number of Geophysical disasters)				0.0272	
				(0.0203)	
L.Log (1+ Number of Climatic disasters)					-0.0038+
					(0.0021)
Controls (Table 3)	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Cluster of S.E.	County	County	County	County	County
Observation	32643	32643	32643	32643	32643
R-squared	0.1188	0.1174	0.1183	0.1171	0.1173
	(1)	(2)	(3)	(4)	(5)
Panel B: Below 100 miles sample					
Dependent variable			P(Deal=1)		
	Margin	Margin	Margin	Margin	Margin
L.Log (1+ Number of disasters)	-0.0037**				
	(0.0012)				
L.Log (1+ Number of Hydrological disasters)		-0.0016			
		(0.0013)			
L.Log (1+ Number of Meteorological disasters)			-0.0026*		
			(0.0011)		
L.Log (1+ Number of Geophysical disasters)				-0.0006	
				(0.0317)	
L.Log (1+ Number of Climatic disasters)					-0.0021
					(0.0017)
Controls (Table 3)	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Cluster of S.E.	County	County	County	County	County
Observation	33182	33182	33182	33182	33182
R-squared	0.2118	0.2109	0.2114	0.2108	0.2109

Notes: Robust standard errors are reported in parentheses: +p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001

Table 8: Deal premium in target samples

	(1) premium_bv	(2) premium_bv	(3) premium_bv	(4) premium_bv
Log (1+ Number of disasters)	0.0631**	0.0500*	0.0627*	0.0516+
	(0.0195)	(0.0204)	(0.0289)	(0.0280)
Product focus		-0.3145***	-0.2325***	-0.1760***
		(0.0337)	(0.0444)	(0.0519)
Geography diversification		-0.0574+	-0.0063	-0.0023
		(0.0311)	(0.0390)	(0.0394)
Relative asset growth			0.0003	0.0001
			(0.0003)	(0.0003)
Cash pay			-0.2687***	-0.2512***
			(0.0327)	(0.0293)
Relative size			-0.1930***	-0.2048**
			(0.0581)	(0.0629)
Relative profit			0.0013	0.0023
			(0.0023)	(0.0018)
Relative capital adequacy			-0.1822***	-0.1560***
			(0.0438)	(0.0440)
Weighted nonperforming loan			-9.5211***	-9.4465***
			(1.0650)	(1.0387)
Constant	0.8211***	0.9900***	1.3855***	0.5289
	(0.0697)	(0.0806)	(0.1488)	(0.3803)
Observations	2569	2540	1567	1567
R-squared	0.2187	0.2878	0.3621	0.4104

Notes: Robust standard errors are reported in parentheses: +p $<$ 0.1, *p $<$ 0.05, **p $<$ 0.01, ***p $<$ 0.001

Table 9: After M&A synergies

		ROA			ROE			Tier 1 Capital			Tier 2 Capital			Leverage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Treated	0.00044***	0.00046***	0.00042***	0.0037***	0.0038***	0.0034**	-0.00017	-0.000082	0.000088	0.00048*	0.00044*	0.00034+	-0.0037***	-0.0034***	-0.0038***
	(0.00011)	(0.00011)	(0.00011)	(0.0011)	(0.0011)	(0.0011)	(0.00036)	(0.00036)	(0.00036)	(0.00019)	(0.00019)	(0.00019)	(0.00072)	(0.00072)	(0.00072)
Event_start	0.00045***			0.0032**			-0.0015**			0.0013*			-0.0011		
	(0.00012)			(0.0011)			(0.00056)			(0.00056)			(0.00095)		
Treated#Event_start	0.00029			0.0015			0.0040**			-0.0026**			0.0052+		
	(0.00030)			(0.0026)			(0.0015)			(0.00084)			(0.0028)		
Event_[t-1]		0.0011***			0.0098***			0.0029***			0.0024***			-0.0024**	
		(0.00012)			(0.0010)			(0.00055)			(0.00051)			(0.00089)	
Treated#Event_[t-1]		-0.0000021			-0.00052			0.0025			-0.0018*			-0.00096	
		(0.00034)			(0.0025)			(0.0016)			(0.00088)			(0.0028)	
Event_[t+1]			0.000034			-0.0012			-0.0039***			-0.00067*			-0.00065
			(0.00014)			(0.0014)			(0.00054)			(0.00030)			(0.00093)
Treated#Event_[t+1]			0.00066+			0.0072*			-0.00047			0.00019			0.0056*
			(0.00034)			(0.0031)			(0.0012)			(0.00067)			(0.0026)
_cons	0.0087***	0.0085***	0.0087***	0.087***	0.085***	0.086***	0.15***	0.15***	0.15***	0.040***	0.040***	0.040***	0.21***	0.21***	0.21***
	(0.0017)	(0.0017)	(0.0017)	(0.019)	(0.019)	(0.019)	(0.0065)	(0.0064)	(0.0065)	(0.0040)	(0.0039)	(0.0040)	(0.023)	(0.023)	(0.023)
Observations	37343	37343	37343	37339	37339	37339	36404	36404	36404	36385	36385	36385	37282	37282	37282
R-squared	0.33	0.33	0.33	0.46	0.46	0.46	0.46	0.46	0.46	0.70	0.70	0.70	0.69	0.69	0.69

Notes: Robust standard errors are reported in parentheses: +p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001

Table 10: Climate survey

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:				P(Deal)				
	Target sample				Acquirer sample			
	Coef.	Margin	Coef.	Margin	Coef.	Margin	Coef.	Margin
L.Log (1+ Number of disasters)	-0.2184***	-0.0141***	-0.1675***	-0.0138***	-0.1480**	-0.0100*	-0.1030+	-0.0098*
	(0.0448)	(0.0040)	(0.0454)	(0.0040)	(0.0518)	(0.0044)	(0.0530)	(0.0044)
high_timing	-0.3895**	0.0005			-0.2632+	-0.0011		
	(0.1202)	(0.0083)			(0.1375)	(0.0101)		
high_timing#L.Log (1+ Number of disasters)	0.1884***				0.1201+			
	(0.0534)				(0.0629)			
high_happening			-0.1507	0.0128			-0.0886	0.0037
			(0.1232)	(0.0087)			(0.1394)	(0.0104)
high_happening#L.Log (1+ Number of disasters)			0.1125*				0.0533	
			(0.0545)				(0.0632)	
Controls (Table 3)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster of S.E.	County	County	County	County	County	County	County	County
Constant	-4.1607***		-4.1753***		-4.0292***		-4.0594***	
	(0.6323)		(0.6376)		(0.7687)		(0.7823)	
Observation	7613	7613	7613	7613	7435	7435	7435	7435
R-squared	0.1724		0.1710		0.2012		0.2003	

Notes: Robust standard errors are reported in parentheses: +p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001

A Appendix

A.1 Variable definition

Table 11: Description of variables used

Feature	Description	Source/Code
	Panel A: Natural disasters	
Log (1+ # All disasters)	Natural logarithm of one plus total counts of natural disasters that occurred in the county j in year t	SHELDUS
Log (1+ # Hydrological disasters)	Natural logarithm of one plus total counts of hydrological disasters that occurred in the county j in year t	Idem
Log (1+ # Meterogological disasters)	Natural logarithm of one plus total counts of meteorological disasters that occurred in the county j in year t	Idem
Log (1+ # Geophysical disasters)	Natural logarithm of one plus total counts of geophysical disasters that occurred in the county j in year t	Idem
Log (1+ # Climatic disasters)	Natural logarithm of one plus total counts of climatic disasters that occurred in the county j in year t	Idem
Crop damages	Total crop damage in U.S. dollars caused by natural disasters in the county j in year t	Idem
Property damages	Total property damage in U.S. dollars caused by natural disasters in the county j in year t	Idem
Total damages	Sum of crop and property damages in U.S. dollars caused by natural disasters in the county j in year t	Idem
Injuries	Total number of people injured due to natural disasters in the county j in year t	Idem
Fatalities	Total number of people killed due to natural disasters in the county j in year t	Idem
	Panel B: M&A deal and bank-level variables	
Deal dummy	Dummy variable takes value as 1 if there is at least 1 M&A deal happening in county j in year t.	S&P capital IQ
Log(1+Number of Deals)	Logarithm of one plus the total number of deals in county j in year t	Idem
Product focus	A dummy variable equal to one if the merger is considered product focusing	Idem
Geography diversification	A dummy variable equal to one if the merger is considered geographically diversifying	Idem
Relative asset growth	This ratio measures targets' assets growth relative to acquirers' asset growth where asset growth is measured over a 12-month period	Idem
Cash pay	Percentage of payment made in cash out of total deal value	Idem
Relative size	This ratio measures targets' asset size relative to acquirers' asset size	Idem
Relative profit	This ratio measures targets' return on asset relative to acquirers' return on assets	Idem
Relative capital adequacy	This ratio measures targets' tier one capital relative to acquirers' tier one capital	Idem
Weighted nonperforming loans	This ratio measures nonperforming loans of targets and is calculated as nonperforming loans divided by total assets	Idem
ROA	Calculated as net income (ni) divided by total assets (at), measuring the profitability of a bank relative to its total assets.	Bank Compustat
ROE	Calculated as net income (ni) divided by common equity (ceq), measuring the profitability of a bank relative to shareholders' equity.	Idem
Tier 1 Capital	This ratio measures a bank's core capital relative to its risk-weighted assets.	Idem
Tier 2 Capital	This ratio measures a bank's supplementary capital relative to its risk-weighted assets.	Idem
Leverage	Calculated as the sum of debt in current liabilities (dlc) and long-term debt (dltt) divided by total assets (at), indicating the bank's financial leverage.	Idem
Treated	A binary variable identifying the treatment group. It is set to 1 if the difference in disaster records is less than 1, indicating that the target bank experienced a higher level of natural disaster impact compared to the acquiring bank.	Authors' own construction
Event_start	The year of M&A announcement	S&P capital IQ
	Panel C: County-level variables	
Population	Natural logarithm of the total number of people in a county	Bureau of Economic Analysis, US Department of Commerce
Total Employment	Natural logarithm of the total number of jobs in a county which counts both full-time and part-time jobs. It includes wage and salary jobs, sole proprietorships, and individual general partners, but not unpaid family workers nor volunteers	Idem
Personal income	Natural logarithm of income where income is measured in thousands of US dollars	Idem
Education attainment	Weighted average number of years of education, calculated as (Less than high school diploma*8 + High school diploma only*12 + Some college or associate's degree*15 + Bachelor's degree or higher*18)/((Less than high school diploma + High school diploma only + Some college or associate's degree + Bachelor's degree or higher)).	Economic Research Service, US Department of Agriculture
Nonbank_depository _institutions	Total number of nonbank depository establishments operating within each county	County Business Patterns (CBP), U.S. Census Bureau
Nonbank_financial _institutions	Total number of other nonbank financial establishments operating within each county	Idem
HHI	Sum of the squares of the market shares of all banks within a county in a given year. Each bank's market share is determined by dividing its total deposits by the county's total deposits and multiplying by 100.	Federal Deposit Insurance Corporation's (FDIC) Summary of Deposits (SOD)

A.2 Figures

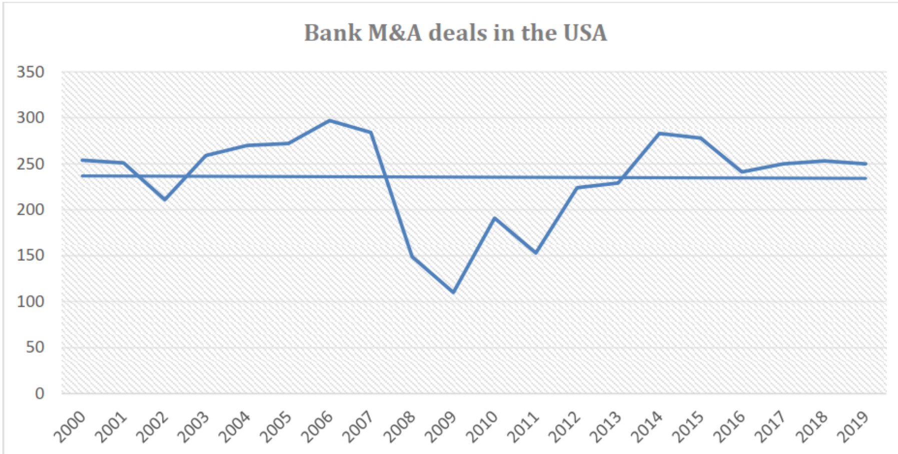

Figure 1: Total number of US bank M&A deals 2000-2019