Natural Disasters and the Role of Regional Lenders in Economic Recovery

Hursit S. Celil, Seungjoon Oh, and Srinivasan Selvam*

July 17, 2021

Abstract

We find that Chinese regional state-owned City-Commercial Banks (CCBs) landlocked by their remit to operate within a city respond to natural disasters more effectively by aggressively expanding credit, especially to corporate borrowers. The credit expansion is more remarkable in CCBs with high state ownership and those that are private. However, the additional lending does not sacrifice asset quality. Moreover, using satellite-based city night lights, we find post-disaster cities that experience greater CCB credit expansion enjoy stronger economic recovery. Overall, our findings highlight the critical role played by regional state-owned lenders in economic recovery from increasingly frequent natural disasters.

Keywords: Natural Disaster, City-Commercial Bank, Recovery

* Hursit S. Celil (hscelil@phbs.pku.edu.cn), Seungjoon Oh (sjoonoh@phbs.pku.edu.cn), and Srinivasan Selvam (sselvam@phbs.pku.edu.cn) are at Peking University HSBC Business School. We are grateful to Duckki Cho, Jongsub Lee, Sung.K. Lee, Heungju Park, Sungbin Sohn, Domenico Tarzia, and the seminar participants at Peking University HSBC Business School for their helpful comments and suggestions. All errors are our own.

1. Introduction

Natural disasters have become more common in frequency and geography, globally (Thomas and López, 2013), and there is a burgeoning literature investigating their economic effects (e.g., Barone and Mocetti, 2014). Even if the severity of disasters remains constant globally, emerging countries with less institutional or environmental protections against natural disasters face the brunt of nature's fury. For example, between 1989 and 2018, natural disasters in China caused 195,820 deaths and direct physical losses of approximately 1.6% of China's GDP compared to 0.57% lost to natural disasters in the U.S and 0.5–1.00% globally (Stern, 2007; Nordhaus, 2010; Zyck, 2013; Feyen et al., 2020).

Tackling the economic fallout from natural disasters is a significant issue as it can have knock-on effects on a wide range of economic decisions.[1] Moreover, climate change, a causative factor for the more frequent natural disasters (Webster et al., 2005), inflicts social and economic losses disproportionately on vulnerable populations and motivates policymakers, business owners, and individuals to draw up contingency plans and responses to minimize its impact. However, the effectiveness of regulatory interventions and how institutional characteristics of credit affect economic recovery following natural disasters is not abundantly clear. .

More specifically, empirical evidence on the effect of natural disasters on credit performance, a key channel used by policymakers for aiding recovery, is mixed. Although natural disasters unarguably stimulate credit demand (e.g., Berg and Schrader, 2012; Cortés and Strahan, 2017; He, 2019), the literature is ambiguous on the performance of increased lending. For example, some studies find that lenders do not face large increases in delinquencies

[1] For example, the 2011 Japanese earthquake and Tsunami are estimated to reduce global GDP by half a percentage point, with half of the reductions expected to affect Japanese economy. The far-reaching economic effects of these disasters included the appreciation of Japanese Yen (JPY) in anticipation of asset repatriations, increase in indebtedness of the government to rebuild infrastructure, reduction in tourism, etc.

following natural disasters (e.g., Cortés, 2004; Gallagher and Hartley, 2017), suggesting that increased lending might optimally aid recovery. Regulators' timely action in relaxing lending restrictions and providing other forms of economic aid can boost economic recovery. Timely interventions, especially in financing liquidity, become extremely crucial to build confidence and avoid panic (e.g., Heide, 2004). Contrarily, Noth and Schüwer (2018) find that in the aftermath of disasters, lenders face increases in non-performing assets and experience shrinking profitability, further supported by other studies (e.g., Albuquerque and Rajhi, 2019).[2] By stressing existing loan portfolios, natural disasters can exert deleterious effects on future lending, further exacerbating the disaster's economic effects. Such heterogeneity in the link between natural disasters and the efficacy of credit complicates policymaker responses to natural disasters and thwarts a potential recovery path for the economy. Moreover, evidence on post-disaster lending, especially in developing countries like China with less institutionalized insurance mechanisms (Jiang et al., 2019) and hence a more vulnerable population, is scant.

Being one of the largest global economies and frequently exposed to natural disasters, China allows its policymakers to experiment with multiple approaches in developing resilience to natural disasters, making it the perfect setting for our study. Hence, we examine how natural disasters in China affect the post-disaster lending activity of City-Commercial Banks (hereafter CCB) in affected areas and its economic consequences. Although regulators, in general, relax lending constraints to aid recovery, private lenders face disincentives in lending to borrowers with reduced capacity vis-à-vis more leeway to lend. Furthermore, large lenders operating in multiple regions enjoy more choice in allocating capital across regions (e.g., Cortés and Strahan,

[2] Noth and Schüwer (2018) document the inadequacies of financial aid programs and insurance in the aftermath of hurricane Katrina in 2005 in the United States as evidenced by increases in non-performing assets and shrinking profitability of lenders. Such negative spillover on lenders are further supported by other studies such as Albuquerque and Rajhi (2019) and Bos, Li, and Sanders (2018).

2017). Thus, in this study, we focus on regional state-owned CCBs, who are arguably more sensitive to the disaster because of their geographic concentration and have more aligned social and economic objectives due to state ownership (refer to Section 2 for the institutional features of CCBs). Also, examining within-country data on disasters allows for rich and more comparable analyses of disasters' economic effects.

Using hand-collected data on CCBs and data on natural disasters from the Emergency Events Database (EM-DAT), we find that CCBs in cities that experience natural disasters with substantial negative economic impact expand credit aggressively. Controlling for other determinants of loan growth, a one-standard-deviation increase in disaster intensity increases loan growth by 7.5 percentage (coefficient of 0.006 times the standard deviation of disaster intensity of 2.546, scaled by the mean loan growth of 0.204), which is economically large. For identification, we rely on multiple fixed effects, including those at the city, year, and bank levels along with first-differenced dependent variable, which allows us to isolate the shocks to the CCB loan supply from other determinants of loan supply such as demand shocks from borrowers, secular growth in cities, time-invariant differences across banks, and common time trends (e.g., Khwaja and Mian, 2008). Moreover, the inclusion of bank and city fixed effects controls for the expected natural disaster risk, allowing our estimates to capture the effect of unexpected disaster risk on credit supply. Furthermore, to explicitly account for the possibility for cities to differ in their propensities to face natural disasters, thereby affecting economic growth, we follow a propensity-matching approach to match cities with higher disaster propensity to those with lower disaster propensities, and still find the association between natural disasters and loan growth.

When we examine whether the growth in loans predominantly arise from corporate or individual borrowers, we find that our results are stronger among corporate loans (even using the matched sample approach), suggesting that these lenders prioritize corporate lending. Corporate borrowers receiving more credit can also be attributable to the lack of reliable credit history data on individual borrowers in China (e.g., Lu, 2014). However, such preferences have potential implications for post-disaster economic recovery.

Moreover, to understand how the lender's incentives are different based on the control exerted by state ownership, we examine whether our results are related to the level of state ownership and whether they are influenced by the public listing status of the lender. Both in our full sample and matched sample, we find that our results survive only among lenders with higher levels of state ownership and when the lender is not publicly listed, suggesting that the extent of control exerted by the state determines the sensitivity of loan growth to disasters.

Finally, we examine the loan performance and economic recovery following disasters. We find that the CCBs with greater post-disaster credit expansion experience a decrease in non-performing assets in the subsequent years, rejecting the view that the increased lending coincides with loosening credit standards. We also find that post-disaster growth as measured by city night lights or through official GDP statistics is higher in cities that witness high CCB loan growth after disasters when compared to cities that witness low CCB loan growth after disasters. Controlling for other determinants in the sample of cities witnessing high CCB loan growth, a one-standard deviation increase in disaster intensity increases city night lighting by 13.24 percentage-points (coefficient of 0.052 times the standard deviation of disaster intensity of 2.546) and official GDP by 1.02 percentage-points (coefficient of 0.004 times the standard deviation of disaster intensity of 2.546), both of which are economically meaningful when compared to the sample means of night lighting and GDP growth of 6.9% and 9.5%, respectively. The outsized effect of CCB lending on night light growth than nominal GDP growth may be due to the reduced pressure on local politicians to post aggressive GDP growth numbers following disasters as other social objectives such as recovery and aid take prominence in disaster-affected cities. However, the growth in city night lights provides a clearer picture of the city's growth without the confounding effect of local politician incentives in reporting official GDPs. These findings suggest that the CCB loans, especially to businesses, following a disaster can be an important channel in aiding disaster-struck regions' recovery.

By showing microeconomic evidence on creditors' disaster response, our study complements the disaster recovery literature where multiple studies focus on household outcomes (e.g., Sawada and Shimizutani, 2008; Hsueh, 2019). For example, Berg and Schrader (2012) document a simultaneous increase in credit demand and credit rationing following volcanic eruptions. Our findings show that alternative ownership and market structures can mitigate the rationing, thereby supporting local businesses through additional credit. Such actions can aid rapid economic recovery, potentially through corporate investment and local employment opportunities. Koetter, Noth, and Rehbein (2020) examine the effect of a single flooding event on lenders and find geographically diversified lenders lend more to affected counties without entailing higher risks. Our evidence shows that even in the absence of geographic diversification or insurance coverage, affected lenders can respond positively to disasters and increase lending without much change in their risk.

Our paper also relates to the growing literature on environmental risk and lending. Many studies find that lenders increasingly incorporate climate risk considerations in their lending and ration credit to high-risk borrowers (e.g., Kling et al., 2019). Our results suggest that regional lenders over-exposed to natural disasters in their main area of operation respond strongly to the disaster through increased lending and play a large role in post-disaster recovery. Also, our findings have implications for the ownership structure and size, and scope of operations of lenders in economic recovery following adverse shocks. Our evidence indicates that small, regional, and state-owned lenders can play a systemically important role in disaster recovery by providing counter-cyclical loan growth, thus promoting financial stability (e.g., Cull and Peria, 2013).

2. Institutional Setting of Chinese City-Commercial Banks

In China, banking institutions are generally divided into policy banks, state-owned large banks, joint-stock banks, city commercial banks (CCBs), rural commercial banks (RCBs), private banks, rural cooperative banks, and rural credit cooperatives. The CCBs are lenders with unique features designed to support local economic development. In 2017, the China Banking and Insurance Regulatory Commission (CBIRC) disclosed that there are a total of 5 large commercial banks, 12 joint-stock commercial banks, 134 CCBs, 1,114 rural commercial banks, 8 private banks, and 40 rural cooperative banks, under its purview. Among these, the CCBs have total assets of 31.7 trillion RMB, which accounts for 12.57% of the total banking sector, and their total borrowings of 29.5 trillion RMB accounts for 12.68% of the total banking sector.[3] However, because of their regional concentration in operations in their cities of association and also operating in smaller cities, CCBs have outsized market shares in their respective cities.

CCBs began with shareholder reforms and pilots based on urban credit cooperatives in 1979. CCBs are joint-stock commercial banks established by local governments, enterprises, and residents (Subrahmanyam, 2011). Unlike larger joint commercial banks, they are allowed to open branches only within their home cities, largely to serve small and medium enterprises

[3] At the end of 2003, the total assets and borrowings of China's CCBs were 1.46 trillion RMB and 1.41 trillion RMB, accounting for 5.29% and 5.31% of the total banking sector, respectively.

operating within the city boundaries. Therefore, their lending activities are regionally concentrated, with CRBC indicating that around 70 percent of the loans from CCBs are granted to small and medium enterprises with the city boundaries (KPMG, 2007). Few of the CCBs have any private investment capital and have largely been used to finance local government projects, thus subject to local government influences. Since their establishment and gradual reforms, CCBs have proven to be a crucial cog in the economy (Gale, 2009). Due to local governments' predominance in the ownership structure, CCBs' objective is to promote the local economy and facilitate government initiatives such as new industry development or local economic structural transformation. By promoting regional development, CCBs play a crucial role in the Chinese commercial banking system with its comparative advantage in understanding the local markets and customers and ensuring balanced growth across the country. The emergence of CCBs has helped improve banking penetration and reduced some of the inefficiencies associated with large state-owned banks, which are bogged down by assets of less efficient large state-owned enterprises (Ferri, 2009).

3. Data and Variable Construction

3.1. Data sources and sample selection

We obtain geographic disaster data from the EM-DAT (Emergency Events Database) database,[4] which includes over 22,000 major disaster events globally since 1900. The database is compiled from various public sources, including UN agencies, non-governmental organizations,

[4] EM-DAT database (http://emdat.be/) is constructed by the Centre of Research on the Epidemiology of Disasters (CRED) at the Universite Catholique de Louvain in Brussels, Belgium under the support of WHO and Belgium government. (Horvath, 2021). Any disaster event which meets one of the following criteria is recorded in the EM-DAT: 1) The disaster event caused 10 or more people deaths, 2) The disaster event caused 100 or more people affected/ injured/ homeless, 3) Declaration by the country of a state of emergency and/ or an appeal for international assistance.

insurance companies, research institutes, and press agencies. In EM-DAT, disasters are grouped into natural disasters and technological (manmade) ones. Natural disasters include geophysical (e.g., earthquake, volcanic activity), meteorological (e.g., storm, extreme temperature and fog), hydrological (e.g., flood, landslide and wave action), climatological (e.g., drought, glacial lake outburst and wildfire), biological (e.g., epidemic, insect infestation, animal accident), and extraterrestrial events. We restrict attention to natural disasters with substantial impact, i.e., when the estimated economic damages are above 100 million U.S. dollars. We merge the disaster data with hand-collected data on 96 City-Commercial Banks or CCBs for the sample period 2007-2017. Our final sample consists of 2,855 disasters at the city-year level that have a substantial economic impact. We also hand collect and obtain city-level macro data, including GDP, fiscal revenue, and expenditure from cities' annual statistical yearbook. To measure a city's economic growth more precisely and overcome concerns regarding local government incentives to window-dress economic performance (Fang, Liu, and Zhou, 2020), we also use satellite night light data obtained from the U.S. NOAA database to estimate city economic growth.

3.2. Summary Statistics

Figure 1 presents the time trends of natural disasters in China during 1980 to 2017. The number of natural disasters have been steadily becoming more frequent. Particularly, the number of natural disasters in China with the estimated economic damages over 100 million U.S. dollars also demonstrate an increasing trend. Table 1 presents summary statistics for our main sample consisting of 766 bank-city-year observations, corresponding to 89 cities over our sample period of 11 years. An average city in our sample experiences 2.9 disasters each year with an estimated

683 lives lost and an economic loss of 2.4 billion USD per disaster, highlighting both the prevalence of natural disasters and their substantial economic impact.

The average CCB in our sample has assets valued at 11.3 billion CNY (around 1.7 billion USD). Our sample CCBs grow their loans on average at 20.4 percent during our sample period, suggesting the growing importance of regional lenders in China. Both household and corporate loans show positive annual growth rates of 30.1 percent and 19.8 percent, respectively. The average ratio of total loan to total deposit (LDR) of CCBs is 59.3 percent, which is lower than the average loan-to-deposit ratio of top commercial banks in China that average over 80 percent during 2014 to 2018 (e.g., Ahmed, 2020) and even US banks which average 70 percent in 2017 (Tor and Sikandar, 2020).

4. Natural Disaster and CCB Loan Growth

4.1. Empirical Specification

Natural disasters unambiguously increase the demand for credit to aid reconstruction and recovery (e.g., Berg and Schrader 2012). However, whether creditors are willing to lend and their circumstances can vary according to the exposure of their incumbent portfolio to the disaster and the credit risk of the new borrower. For example, Nguyen and Wilson (2020) find that although the aggregate credit lending decreases following the 2004 tsunami in Thailand, the effect is somewhat weaker when lenders have physical branches in the affected areas or the disaster intensity is less severe. Their conditional findings suggest a tentative link between local presence and credit availability in the aftermath of natural disasters. To investigate this more thoroughly, we use our broader sample of natural disasters and sample of land-locked CCBs and estimate the following specification:

$$Loan\ Growth_{i,j,t} = \alpha \cdot Disaster\ Intensity_{j,t\text{-}1} + \beta \cdot X_{i,j,t} + \delta_i + \delta_j + \delta_t + \varepsilon_{i,j,t} \quad (1)$$

where *i*, *j*, and *t* represent bank, city, and year, respectively. The dependent variable, $Loan\ Growth_{i,j,t}$, is the difference between total CCB loans in year *t* and year *t*-1 scaled by total loans in year *t-1*. The main independent variable is the city-level disaster intensity in year *t*-1, measured as the total number of disasters with substantial economic impact. We control for city-specific control variables such as GDP level and fiscal surplus, bank-specific characteristics such as return on assets, loan to deposit ratio, size (total assets), and equity to assets ratio.

Moreover, we also include the bank (δ_i), city (δ_j), and year fixed effects (δ_t), to capture bank- and city-specific time-invariant unobservable characteristics as well as common time trends. These fixed effects allow us to isolate the shocks to the CCB loan supply from demand shocks in disaster-affected cities. City-specific credit demand shocks are absorbed by the combination of city and year fixed effects (e.g., Khwaja and Mian, 2008). Any time-invariant bank characteristics such as secular growth in individual banks will be absorbed by the bank fixed effects. Thus, the coefficient estimate of *Disaster Intensity* parsimoniously captures the CCB lending response to the natural disaster, allowing us to interpret a causal relationship.

4.2. Baseline Findings

Panel A of Table 2 represents the baseline estimates of the effects of natural disasters on CCB lending. All specifications include city and year fixed effects controlling for any demand shocks that the CCBs face in their operating cities. Columns (1)–(2) without and with bank fixed effects report similar estimates for the coefficient on *Disaster Intensity*, significant at least at the 5 percent level. These findings indicate that following disasters, CCBs increase their lending significantly compared to pre-disaster years. In terms of economic magnitude, a one-standard-deviation increase in *Disaster Intensity* leads to a 7.5 percent increase in loan growth (=0.006×2.546/0.204) or a 1.5 percentage points increase in loan growth (=0.006×2.546). Compared to the average and standard deviation of loan growth of 20.4% and 10.1%, the 1.5 percentage point increase is an economically meaningful increase in amount of loans. These findinds are all the more remarkable because these disasters while increasing the loan demand also do affect the solvency of borrowers negatively. Thus, our findings might be biased lower due to the decrease in creditworthiness of borrowers affected adversely by the natural disaster.

Our results are robust to in columns (3) and (4) for the inclusion of city and bank level control variables that can determine loan growth of a CCB such as the GDP of the city, the fiscal surplus of the local government, and the size, capitalization, and profitability of the the CCBs. . Among the control variables, the equity-to-asset ratio of the bank is positively associated with the loan growth amount in column (3), suggesting that having partialled out the independent effect of the natural disaster, well-capitalized banks lend more aggressively. In column (4) with bank fixed effects included, however, size of the CCB is strongly related to loan growth after partialling out the effects of the disaster. Overall, these results suggest that given an unexpected shock in the form of natural disasters, local CCBs increase credit supply to local businesses and consumers to cope with these events' negative impact.[5] These findings are intriguing because, despite the adverse shock to their incumbent portfolio which is made more severe by their geographic restrictions in lending and the credit risk of borrowers, local lenders seem to adopt an '*all or bust*' approach in their lending.

4.3. Propensity-Score Matching Approach

[5] Redefining loan growth rate from year *t*-2 to year *t* to avoid confounding effect of disaster disruption to lending provides similar results.

A potential concern with these findings is that economic conditions in cities that are frequently ravaged by disasters may be starkly different from those that are less exposed to disasters. For example, cities located on river banks might be more prone to flooding and their lenders might already price that risk in their lending decisions. Although our use of city fixed effects mitigates some of these concerns, it is still feasible that some disaster-prone city has under exploited economic opportunities consistently, thereby increasing CCB willingness to lend especially post large disasters when governments pay attention to disaster mitigation activities. Thus, to alleviate such remaining concerns, we follow a propensity-score (nearest neighborhood) matching approach and compare the loan growth of lenders from high disaster-prone areas and low disaster-prone areas. Specifically, we estimate the probability (i.e., propensity score) of a city facing a natural disaster using the city's economic characteristics and time and city fixed effects by regressing an indicator for disaster intensity, i.e., *High Disaster Intensity* (defined as greater than sample median) on city characteristics, including its gross domestic product (*Log (City GDP)*), its fiscal gap (*City Budget Surplus*), mean CCB characteristics including total assets (*Size*), equity-to-assets ratio (*Equity / Assets*), return on assets, and loan to deposits ratio, and indicators for city and year, respectively. We then match, without replacement, a city with a higher disaster probability with another with a lower probability. The matched sample consists of 212 CCBs bank-year observations in 65 and 67 city-years with high and low disaster probabilities, respectively, which are largely similar along observable dimensions of city and bank characteristics. Although we follow neighborhood one-on-one matching, the number of city-years in the treated and control sample are different due to the possibility for more than one CCB to be based out a city.

Our matching minimizes the difference between cities with different disaster intensities, which is confirmed in Panel B of Table 1, where we report the differences in mean and median matching variables between the treated and control groups. We find that none of the differences are significant, suggesting that the matching has identified similar cities on observable characteristics. This mimizes the concern that our findings may be driven by observable characteristics that are different between regions with different disaster propensities.

Panel B of Table 2 presents the estimation results in Panel A but using only a matched sample of cities with high and low lagged disaster propensities. As in Panel A, we include fixed effects and control variables in all the corresponding specifications. We still find that the coefficient on *High Disaster Intensity* remains significant at the 5 percent level across all the four specifications, mitigating the concern that our findings are driven by disaster frequency being correlated with economic conditions. Furthermore, we find that the magnitude of the coefficient is almost three and a half times larger than that in the unmatched sample, suggesting that the original estimates are biased lower due to differences in disaster intensities across cities.

4.4. Robustness Tests

We further examine whether CCBs sensitivity to natural disasters are affected by the scale of the disaster. To that extent we decompose our *Disaster Intensity* measure into a *High Damage Disaster Intensity* and *Low Damage Disaster Intensity* measures based on the sample median of economic damanges. Using these two measures, we repeat the analyses in Table 2 and present the findings in Panel A of Table 3. We find that both these measures are significantly related to loan growth of CCBs with similar magnitude of coefficients. If CCBs are reacting proportionately to a natural disaster, then a disaster with excessive economic damages should elicit a greater lending increase. However, our findings seem to indicate that the scale of the disaster is not increasing the lending scale as one would expect. Such a decreased sensitivity to the scale of disaster could be due to several reasons including the disproportionate response of government agencies and large commercial banks to large disasters. Furthermore, outsized disasters might significantly dent viable investment opportunities, thereby not providing attractive lending potential for the CCBs. The lack of meaningful city level data for a large sample of these cities prevents us from exploring these speculative explanation further.

Our sample period also coincides with the 2007-2008 global financial crisis which originated in the subprime lending markets in the United States before spreading to other countries. Export-oriented and global supply chain related industries in China suffered the wrath of the crisis induced slowdown around the world. For example, Liu (2009) estimates that a 1 percent decline in growth in the developed economies during the global financial crisis will translate to a 0.73 percent slowdown of the Chinese economy. To counteract this, the Chinese government in November of 2008 implemented a $ 586 billion stimulus package to reinvigorate the economy (Morrison, 2009). Thus, it is conceivable that some of our findings might be affected by the financial crisis and the subsequent responses of governments around the world. To mitigate this concern, we exclude the crisis years and reestimate our regressions in Table 2. We present the findings in Panel B of Table 3. Our results using the smaller sample of disasters and non-crisis post-disaster years are qualitatively similar to those in Table 2.

5. Cross-sectional Heterogeneity in CCB Loan Growth

5.1. Loan Allocation between Corporate and Household Borrowers

To further understand the nature of these post-disaster credit supply, in Table 4, we examine who receives more of the credit between corporate and household borrowers. Based on the CCB provided bifurcation in their lending data between corporate and household borrowers, we estimate our regressions based on the growth rates for these subgroups of lenders. In Panel A of Table 4, the results indicate that increased CCB lending is significantly associated with corporate loan growth in columns (1)–(2), but the relation is insignificantly positive in the sample that consists of households. Our finding does not, however, suggest that the government or the lenders let the households tide over the crisis themselves. But perhaps, our findings may indicate that credit is made more available to more formal borrowers, whereas households may be receiving aid in other forms such as direct payments, etc.

Furthermore, the lack of reliable centralized credit history for individuals and CCB mandates to support local businesses may also explain these differences among borrowers' growth. Since corporations can payoff borrowings easily upon economic recovery in the form of taxes and repayments, authorities reach out to businesses via the credit supply channel.

In Panel B of Table 4, we repeat the analysis using the propensity-score matched sample to minimize the influence of any difference in cities' propensity for natural disasters and find qualitatively similar results. Overall, our findings in Table 4 indicate that the lenders prioritize corporate borrowers in the aftermath of natural disasters.

5.2. Natural Disaster, State-Ownership and Loan Growth

Like the ownership structure in many areas of the economy, CCBs' ownership structure may also be influenced by local and central government incentives to promote the strength and stability of the local economy to face unanticipated economic shocks. To examine this phenomenon, we test whether the ownership structure of CCBs in the form of state and non-state yields any cross-sectional variation in post-disaster lending and recovery. In Panel A of Table 5, we find that lenders with greater state ownership and those that are private show higher sensitivity to disasters in increasing lending, suggesting that government control is a potential driver of disaster-driven lending increases. Higher ownership and non-public listing status allow the state to impose more control on these banks, making them more responsive to the disaster. The CCBs with a public listing or low state ownership suffer from more severe twin agency problems (e.g., Stulz, 2005) and hence may be less responsive to natural disasters. Panel B of Table 5 using the propensity-score matched sample from Table 2 yields similar results.

6. Natural Disaster, CCB Loan Performance, and Disaster Recovery

6.1. Natural Disaster and CCB Loan Performance

Next, we investigate whether the credit supply helps mitigate the negative effects of natural disasters. First, we examine the loan performance to assess the micro effects of the increased lending. We subsequently investigate the city-level economic recovery to throw light on the macro effects of CCB responses. In Table 6 Panel A, we find that the CCB's loan performance, measured as the ratio of non-performing loans (%), significantly improves after their post-disaster period credit expansion as the interaction term between *Disaster Intensity* and an indicator *High CCB Loan Growth* is significantly negative in three of the four post-disaster periods. The results are particularly evident in years *t*+1 and *t*+2 among the post-disaster years. Having partialled out the effect of aggressive post-disaster CCB lending, higher CCB lending and disaster intensities increase non-performing loans. Thus, these findings indicate that increasing lending by CCBs during the post-disaster years may be rational as their economic fortunes are tied to the city’s growth despite the adversities

6.2. Natural Disaster, CCB Loan Growth and Disaster Recovery

Finally, we examine the role of the local lenders in economic recovery by examining the city-level economic recovery. Night lights are a valuable proxy of economic activity at the regional level when GDP data are lacking or of poor quality (Bickenbach et al., 2016). We present the findings of our analyses in Table 7. Specifically, we split the city-years into two subsamples based on the rate of CCB loan growth in these cities. Using the two subsamples, we estimate the effect of disaster intensity on economic growth based on both state declared official GDP numbers and those based on change in night lights.

Using both the measures, we find that cities that have had recent disasters experience strong economic growth when the CCB loan growth is strong in these cities (i.e., columns (1) and (3)). In terms of economic magnitude, in the sample of cities witnessing high CCB loan growth, a one-standard deviation increase in disaster intensity (by 2.546) increases city night lighting by 13.24 percentage-points (=0.052×2.546) and official GDP by 1.02 percentage-points (=0.004×2.546). The disparity in these economic effects might be due to the distortion in official figures due to career concerns of local politicians (e.g., Chen, Li, and Lu, 2018). For example, natural disasters might disincentivize the local politician from exaggerating economic performance which could happen during normal periods, thereby allowing the GDP to be more truthful (and thus growth to be lower). The growth in city night lights is devoid of these incentives induced distortions in the economic data, and thus provides a clearer picture of the city's growth. However, in the sample where the loan growth of CCBs is below sample median (columns (2) and (4)), we find that disaster intensity has mixed effect on economic growth. For example, the official GDP growth figures are positively associated with disaster, significant at the 10 percent level. However, city night light growth is unaffected by disaster. Overall, the results in Table 7 show that the CCB loans following a disaster can be an important channel in aiding disaster-struck regions' recovery.

7. Conclusion

This study examines how state-owned regional lenders respond to natural disasters with substantial economic impact and consequences for post-disaster economic recovery. Using data on CCBs and natural disasters in China, we find that disaster-exposed CCBs increase their lending activity, especially to corporate borrowers, with the effect increasing in the degree of control of the lender by the state. The lending increases are associated with increased asset quality and economic outperformance in the affected cities. Our identification comes from the use of multiple fixed effects, including city, bank, and year fixed effects which accounts for any potential demand shocks across the cities, allowing us to interpret our findings as arising from the sensitivity of local lenders to unexpected natural disasters. Overall, our results highlight regional lenders' constructive role in coping with natural disasters' economic effects, which is more important as these events' frequency increases globally.

References

Ahmed, A.A.A., 2020. Corporate attributes and disclosure of accounting information: Evidence from the big five banks of China. *Journal of Public Affairs*, e2244.

Albala-Bertrand, J.M., 1993. Natural disaster situations and growth: A macroeconomic model for sudden disaster impacts. *World Development*, 21: 1417-1434.

Albuquerque P. H., and Rajhi W., 2019. Banking stability, natural disasters, and state fragility: Panel VAR evidence from developing countries. *Research in International Business and Finance*. 50:430-43.

Barone G. and Mocetti S., 2014. Natural disasters, growth and institutions: a tale of two earthquakes. *Journal of Urban Economics*, 84:52-66.

Berg, G. and Schrader, J., 2012. Access to credit, natural disasters, and relationship lending. *Journal of Financial Intermediation*, 21:549-568.

Bickenbach, F., Bode, E., Nunnenkamp, P., and Söder, M., 2016. Night lights and regional GDP. *Review of World Economics*, 152: 425-447.

Chen, Y.J., Li, P. and Lu, Y., 2018. Career concerns and multitasking local bureaucrats: Evidence of a target-based performance evaluation system in China. *Journal of Development Economics*, *133*, pp.84-101.

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

Cull, R. and Peria, M.S.M., 2013. Bank ownership and lending patterns during the 2008–2009 financial crisis: Evidence from Latin America and Eastern Europe. *Journal of Banking & Finance*, 37: 4861-4878.

Fang, H., Liu, C., and Zhou, L.A., 2020. Window Dressing in the Public Sector: A Case Study of China's Compulsory Education Promotion Program. *NBER Working Paper*.

Ferri, G., 2009. Are New Tigers supplanting Old Mammoths in China's banking system? Evidence from a sample of city commercial banks. *Journal of Banking and Finance,* 33: 131-140.

Feyen, E., Utz, R., Zuccardi Huertas, I., Bogdan, O., and Moon, J., 2020. Macro-financial aspects of climate change. *The World Bank*.

Gale, F., 2009 Financial Reforms Push Capital to the Countryside. *The Chinese Economy*, 42: 58-78.

Gallagher, J., and Hartley D. 2017. Household finance after a natural disaster: The case of Hurricane Katrina. *American Economic Journal: Economic Policy* 3:199-228.

He, A., 2019. Spillovers of natural disaster strikes through bank-firm networks: Loan- and firm-level evidence of financial constraints. *Working Paper*.

Heide, E.A., 2004. Common misconceptions about disasters: Panic, the disaster syndrome, and looting. The first 72 hours: A community approach to disaster preparedness, 337.

Horvath, R., 2021. Natural catastrophes and financial depth: An empirical analysis. *Journal of Financial Stability*, *53*, p.100842.

Hsueh, H.Y., 2019. The role of household social capital in post-disaster recovery: An empirical study in Japan. *International Journal of Disaster Risk Reduction,* 39:101199.

Jiang, Y., Luo Y., and Xu X., 2019. Flood insurance in China: recommendations based on a comparative analysis of flood insurance in developed countries. *Environmental Earth Sciences,* 78:93.

Khwaja, A.I. and Mian, A., 2008. Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review*, *98*(4), pp.1413-42.

Kling, G., Volz U., Murinde V., and Ayas S., 2019. The impact of climate vulnerability on firms' cost of capital and access to finance. *Working Paper*.

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

KPMG, 2007, China's city commercial banks: Opportunity knocks, Hong Kong

Liu, L., 2009. Impact of the global financial crisis on China: Empirical evidence and policy implications. *China & World Economy*, *17*(6), pp.1-23.

Lu, R., 2014, Why There Are No Credit Scores in China, ForeignPolicy.com

Morrison, W.M., 2009. China and the global financial crisis: Implications for the United States. Library of Congress Washington DC Congressional Research Service.

Nguyen, L. and Wilson, J.O., 2020. How does credit supply react to a natural disaster? Evidence from the Indian Ocean Tsunami. *European Journal of Finance*, *26*(7-8), pp.802-819.

Nordhaus, W. D., 2010. The economics of hurricanes and implications of global warming. *Climate Change Economics* 1: 1–20.

Noth F. and Schüwer, U., 2018. Natural Disaster and Bank Stability: Evidence from the U.S. Financial System. Working Paper.

Sawada Y. and Shimizutani, S., 2008. How do people cope with natural disasters? Evidence from the Great Hanshin-Awaji (Kobe) earthquake in 1995. *Journal of Money Credit and Banking*. 40:463-88.

Stern, N., 2007. The economics of climate change: The Stern review. Cambridge University Press.

Subrahmanyam, V., 2011. City and rural commercial banks in China: The new battlefield in Chinese banking. China Research Center, 11.

Stulz, R.M., 2005. The limits of financial globalization. *Journal of Finance*, 60: 1595-1638.

Tor, M. and Sikandar, A.S. 2020, June 25. Loan-to-deposit ratio at US banks hits 29-year low as transaction accounts surge. S&P Global Market Intelligence. http://www.spglobal.com/marketintelligence/en/news-insights/latest-news-headlines/loan-to-deposit-ratio-at-us-banks-hits-29-year-low-as-transaction-accounts-surge-59103892

Thomas V. and López R., 2015. Global increase in climate-related disasters. *Asian Development Bank Economics Working Paper*.

Webster, P. J., Holland, G. J., Curry, J. A., and Chang, H.-R., 2005. Changes in tropical cyclone number, duration, and intensity in a warming environment. *Science* 309: 1844–1846.

Zyck, S.A., 2013, Crisis preparedness and response: the Chinese way, *Overseas Development Institute*

Figure 1. Trends of Natural Disasters in China

The figure presents the time trends of natural disasters from 1980 to 2017. The solid line shows the total number of natural disasters. The dashed line shows the total number of natural disasters with estimated economic damages exceeding 100 million U.S. dollars.

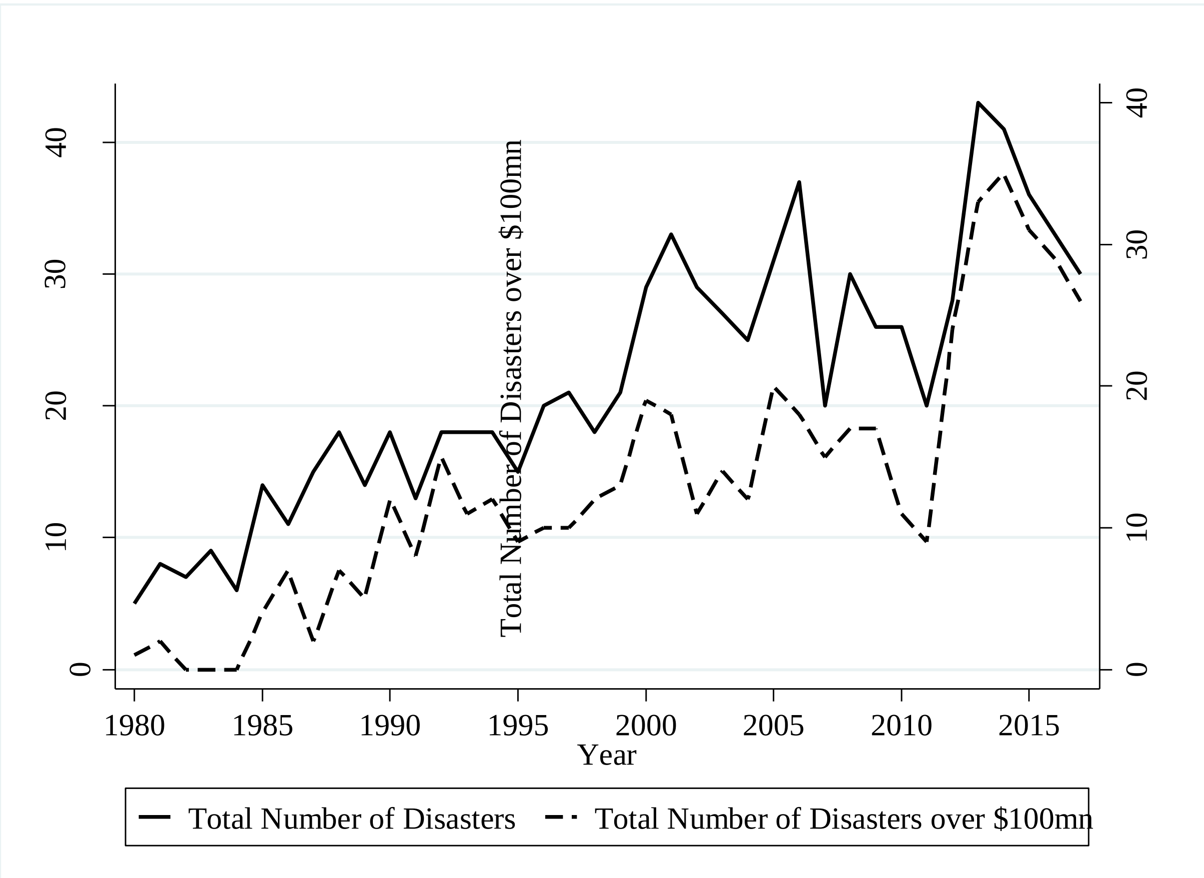

Table 1. Summary Statistics

The table presents summary statistics for our main analysis. The detailed descriptions of all the variables are available in the Appendix.

Panel A. Descriptive Statistics for Full Sample

	Mean	SD	10th	Median	90th	Obs.
Disaster Intensity	2.920	2.546	1.000	2.000	7.000	766
Estimated Economic Loss ($bn)	2.337	4.787	0.234	1.114	3.644	766
Deaths (000s)	0.683	6.522	0.000	0.040	0.163	766
City GDP (¥bn)	322.866	298.132	78.700	221.719	716.451	766
City Budget Surplus	-0.815	0.798	-1.882	-0.548	-0.115	766
City-Commercial Bank (CCB) Characteristics						
Loan Growth	0.204	0.101	0.090	0.192	0.328	766
Size (total assets ¥bn)	11.255	14.297	1.700	6.400	26.000	766
Equity / Assets	0.072	0.028	0.050	0.070	0.090	766
Return on Assets	0.011	0.004	0.006	0.011	0.017	766
Loan / Deposits	0.593	0.109	0.460	0.603	0.720	766
Corporate Loan Growth	0.198	0.129	0.054	0.190	0.349	564
Household Loan Growth	0.301	0.376	0.000	0.250	0.651	564
City Lighting Growth	0.069	0.214	-0.166	0.047	0.346	409
City GDP Growth	0.095	0.083	0.017	0.095	0.186	761

Panel B. Descriptive Statistics for Propensity Score-Matched Sample

	Treated Sample (N = 212): a		Control Sample (N = 212): b		Test of Mean Difference and *t*-statistics (a - b)	
	Mean	Median	Mean	Median	Difference	*t*-stat
Log (City GDP)	5.43	5.43	5.51	5.53	0.08	1.12
City Budget Surplus	-0.72	-0.39	-0.78	-0.51	-0.06	-0.81
Size	2.04	1.74	2.08	2.14	0.04	0.54
Equity / Assets	0.07	0.07	0.07	0.07	0.00	0.46
Return on Assets	0.01	0.01	0.01	0.01	-0.00	-1.55
Loan / Deposits	0.60	0.62	0.60	0.61	-0.00	-0.29

Table 2. Natural Disaster and CCB Loan Growth

This table presents results from the OLS regressions that test the effects of the disaster intensity on CCB loan growth. In Panel A, the sample consists of 765 bank-year observations during our sample period from 2007 to 2017. The dependent variable is *Loan Growth*$_t$, the difference between total CCB loans in year *t* and year *t*-1 scaled by total loans in year *t*-1. *Disaster Intensity*$_{t-1}$ is the city-level disaster intensity in year *t*-1, measured as the total number of disasters with substantial economic impact. In Panel B, we use a propensity-score (nearest neighborhood) matching approach that consists of 212 bank-year observations with an above-median *Disaster Intensity* and 212 bank-year observations with a below-median *Disaster Intensity* from 2007 to 2017. We estimate the lagged probability (i.e., propensity score) of a city facing a natural disaster using the city's economic characteristics and time and city fixed effects by regressing an indicator for disaster intensity (defined as greater than sample median) on city characteristics, including its gross domestic product (*Log (City GDP)*), its fiscal gap (*City Budget Surplus*), mean CCB characteristics including total assets (*Size*), equity-to-assets ratio (*Equity / Assets*), return on assets, and loan to deposits ratio, and indicators for city and year, respectively. We then match, without replacement, a city with a higher lagged disaster probability with another with a lower probability. *High Disaster Intensity* is an indicator that takes the value of one for a treatment sample (defined as greater than sample median *Disaster Intensity*) and zero for a control sample (defined as greater than sample median *Disaster Intensity*). The detailed descriptions of other variables are available in the Appendix. *t*-statistics are reported in parentheses and are based on standard errors clustered by cities. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A. OLS Regressions with City and Bank Fixed Effects

	Loan Growth$_t$			
	(1)	(2)	(3)	(4)
Disaster Intensity	0.006**	0.006***	0.006***	0.006***
	(2.60)	(2.63)	(2.83)	(2.81)
Log (City GDP)			0.022	0.019
			(0.45)	(0.43)
City Budget Surplus			-0.035	-0.037*
			(-1.59)	(-1.67)
Size			0.018	0.054***
			(0.82)	(2.89)
Equity / Assets			0.238*	0.186
			(1.97)	(1.38)
Return on Assets			2.160	2.655*
			(1.19)	(1.75)
Loan / Deposits			-0.028	-0.005
			(-0.39)	(-0.06)
City Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	No	Yes
Observations	765	765	765	765
Adjusted R-squared	0.313	0.248	0.323	0.269

Panel B. Using a Propensity-score Matched Sample

	Loan Growth$_t$			
	(1)	(2)	(3)	(4)
High Disaster Intensity	0.022**	0.021**	0.024**	0.024**
	(0.010)	(0.010)	(0.010)	(0.010)
Controls in Panel A	Yes	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	No	Yes
Observations	411	411	411	411
Adjusted R-squared	0.326	0.217	0.344	0.244

Table 3. Natural Disaster and CCB Loan Growth: Robustness Tests

This table presents results from the OLS regressions that test the effects of the disaster intensity on CCB loan growth. In Panel A, we decompose *Disaster Intensity*$_{t-1}$ into *High Damage Disaster Intensity*$_{t-1}$ and *Low Damage Disaster Intensity*$_{t-1}$ based on the sample median. We use 765 bank-year observations from 2007 to 2017. In Panel B, the sample consists of 602 bank-year observations for our sample period from 2007 to 2017 excluding financial crisis period 2008-2009. The dependent variable is *Loan Growth*$_t$, the difference between total CCB loans in year *t* and year *t*-1 scaled by total loans in year *t*-1. *Disaster Intensity*$_{t-1}$ is the city-level disaster intensity in year *t*-1, measured as the total number of disasters with substantial economic impact. The detailed descriptions of other variables are available in the Appendix. *t*-statistics are reported in parentheses and are based on standard errors clustered by cities. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A. Decomposing *Disaster Intensity* into *High Damage Disaster Intensity* and *Low Damage Disaster Intensity*

	Loan Growth$_t$			
	(1)	(2)	(3)	(4)
High Damage Disaster	0.005**	0.005*	0.005**	0.005**
Intensity	(0.002)	(0.002)	(0.002)	(0.002)
Low Damage Disaster	0.005**	0.005**	0.006***	0.006***
Intensity	(0.002)	(0.002)	(0.002)	(0.002)
Controls in Table 2	Yes	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	No	Yes
Observations	765	765	765	765
Adjusted R-squared	0.312	0.247	0.322	0.269

Panel B. Excluding Financial Crisis Period (2008-2009)

	Loan Growth$_t$			
	(1)	(2)	(3)	(4)
Disaster Intensity	0.006***	0.006***	0.006***	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)
Controls in Table 2	No	No	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	No	Yes
Observations	602	602	602	602
Adjusted R-squared	0.331	0.226	0.335	0.284

Table 4. Natural Disaster and Loan Allocation

The table presents results from the OLS regressions that test the effects of the disaster intensity on CCB loan allocation. In Panel A, the sample consists of 561 bank-year observations for our sample period from 2007 to 2017. In Columns 1 and 2, the dependent variable is *Corporate Loan Growth$_t$* is the difference between total CCB loans for corporate borrowers in year *t* and year *t*-1 scaled by corporate loans in year *t*-1. In Columns 3 and 4, the dependent variable is *Household Loan Growth$_t$*, the difference between total CCB loans for household borrowers in year *t* and year *t*-1 scaled by household loans in year *t*-1. *Disaster Intensity$_{t-1}$* is the city-level disaster intensity in year *t*-1, measured as the total number of disasters with substantial economic impact. In Panel B, we use a propensity-score (nearest neighborhood) matching approach identical to Table 2. *High Disaster Intensity* is an indicator that takes the value of one for a treatment sample (defined as greater than sample median *Disaster Intensity*) and zero for a control sample (defined as greater than sample median *Disaster Intensity*). The detailed descriptions of other variables are available in the Appendix. *t*-statistics are reported in parentheses and are based on standard errors clustered by cities. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A. OLS Regressions with City and Bank Fixed Effects

	Corporate Loan Growth$_t$		Household Loan Growth$_t$	
	(1)	(2)	(3)	(4)
Disaster Intensity	0.009***	0.009***	0.000	-0.001
	(2.68)	(2.71)	(0.02)	(-0.13)
Log (City GDP)	-0.028	-0.015	0.479**	0.462***
	(-0.46)	(-0.27)	(2.58)	(2.80)
City Budget Surplus	-0.006	-0.008	0.061	0.051
	(-0.18)	(-0.28)	(0.74)	(0.64)
Size	0.047	0.095***	-0.162	0.208**
	(1.43)	(3.41)	(-0.87)	(2.16)
Equity / Assets	0.573***	0.694***	-0.229	0.556
	(2.75)	(3.64)	(-0.27)	(0.84)
Return on Assets	2.228	0.532	-15.007*	-15.577*
	(0.78)	(0.25)	(-1.76)	(-1.82)
Loan / Deposits	-0.146	-0.131	0.362	0.570**
	(-1.33)	(-1.03)	(1.59)	(2.40)
City Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	No	Yes
Observations	561	561	561	561
Adjusted R-squared	0.279	0.175	0.117	0.040

Panel B. Using a Propensity-score Matched Sample

	Corporate Loan Growth$_t$		Household Loan Growth$_t$	
	(1)	(2)	(3)	(4)
High Disaster Intensity	0.029**	0.033**	-0.017	0.012
	(0.014)	(0.014)	(0.030)	(0.031)
Controls in Panel A	Yes	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	No	Yes
Observations	310	310	310	310
Adjusted R-squared	0.230	0.026	0.179	0.147

Table 5. Natural Disaster, State-Ownership and Loan Growth

The table presents results from the OLS regressions that test the cross-sectional variation of the effects of the disaster intensity on loan growth. In Panel A, the sample consists of 765 bank-year observations for our sample period from 2007 to 2017. We consider subsamples of CCB based on the government ownership in Columns 1 and 2 and based on the public status in Columns 3 and 4. *High Government Ownership* is one if the government ownership of CCB is greater than 5% and zero otherwise. Publicly Listed (Private) is one if the CCB is public-listed (private). The dependent variable is *Loan Growth*$_t$, the difference between total CCB loans in year *t* and year *t*-1 scaled by total loans in year *t*-1. *Disaster Intensity*$_{t-1}$ is the city-level disaster intensity in year *t*-1, measured as the total number of disasters with substantial economic impact. In Panel B, we use a propensity-score (nearest neighborhood) matching approach identical to Table 2. *High Disaster Intensity* is an indicator that takes the value of one for a treatment sample (defined as greater than sample median *Disaster Intensity*) and zero for a control sample (defined as greater than sample median *Disaster Intensity*). The detailed descriptions of other variables are available in the Appendix. *t*-statistics are reported in parentheses and are based on standard errors clustered by cities. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A. OLS Regressions with City and Bank Fixed Effects

	Loan Growth$_t$			
	(1)	(2)	(3)	(4)
	High Government Ownership	Low Government Ownership	Publicly Listed	Private
Disaster Intensity	0.004*	0.002	0.004	0.007***
	(1.73)	(0.57)	(0.61)	(2.90)
Log (City GDP)	0.007	0.063	0.002	0.017
	(0.12)	(0.93)	(0.01)	(0.36)
City Budget Surplus	-0.021	0.022	-0.049	-0.036
	(-0.89)	(0.98)	(-0.77)	(-1.57)
Size	0.057**	0.102	0.059	0.049**
	(2.43)	(1.38)	(0.91)	(2.54)
Equity / Assets	-0.007	0.004	0.174	0.146
	(-0.04)	(0.01)	(0.14)	(1.14)
Return on Assets	3.534**	2.122	8.761	2.075
	(2.07)	(0.66)	(1.71)	(1.24)
Loan / Deposits	0.173*	-0.166	0.430**	-0.034
	(1.74)	(-1.46)	(2.20)	(-0.44)
City Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	No	Yes
Observations	425	187	115	650
Adjusted R-squared	0.320	0.227	0.189	0.277

Panel B. Using a Propensity-score Matched Sample

	Loan $Growth_t$			
	(1)	(2)	(3)	(4)
	High Government Ownership	Low Government Ownership	Publicly Listed	Private
High Disaster Intensity	0.011*	0.012	0.002	0.015**
	(0.006)	(0.016)	(0.005)	(0.006)
Controls in Panel A	Yes	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	No	Yes
Observations	217	113	69	349
Adjusted R-squared	0.133	0.061	0.130	0.269

Table 6. Natural Disaster and CCB Loan Performance

The table presents results from the OLS regressions that test the effects of the disaster intensity on CCB loan performance conditional on CCB loan growth. The sample consists of 661 bank-year observations for our sample period from 2007 to 2017. The dependent variable is the average *Non-Performing Loan (NPL)* ratio (%) between year *t*+1 to *t*+3 in Column 1 and bank-year level NPL ratio in each year t+1 to t+3 in Columns 2 to 4, respectively. *High* (*Low*) *CCB Loan Growth* is one if the CCB Loan Growth in year *t* is greater (lower) than the sample median and zero otherwise. *Disaster Intensity*$_{t-1}$ is the city-level disaster intensity in year *t*-1, measured as the total number of disasters with substantial economic impact. The detailed descriptions of other variables are available in the Appendix. *t*-statistics are reported in parentheses and are based on standard errors clustered by cities. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Non-Performing Loan (%)			
	(1)	(2)	(3)	(4)
	Ave. *t*+1 to *t*+3	Year *t*+1	Year *t*+2	Year *t*+3
Disaster Intensity ×	-0.225***	-0.186***	-0.180**	-0.134
High CCB Loan Growth	(0.073)	(0.067)	(0.078)	(0.160)
Disaster Intensity	0.043**	0.053**	0.043**	-0.012
	(0.017)	(0.022)	(0.018)	(0.038)
High CCB Loan Growth	0.324**	-0.190	0.257	0.912***
	(0.161)	(0.212)	(0.208)	(0.265)
Log (City GDP)	-0.196	-0.127	-0.261	-0.465
	(0.235)	(0.308)	(0.440)	(0.502)
City Budget Surplus	0.083	0.059	0.079	0.149
	(0.076)	(0.080)	(0.088)	(0.118)
Size	0.578***	0.464**	0.716***	0.711***
	(0.168)	(0.209)	(0.203)	(0.187)
Equity / Assets	0.108	1.734	-0.642	-2.258
	(1.531)	(1.700)	(2.122)	(2.293)
Return on Assets	-21.106**	-36.648***	-14.845	-2.875
	(10.274)	(11.921)	(13.710)	(13.369)
Loan / Deposits	1.056***	1.071**	1.390***	1.081**
	(0.279)	(0.452)	(0.452)	(0.452)
City Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes
Observations	661	656	568	483
Adjusted R-squared	0.615	0.405	0.427	0.423

Table 7. Natural Disaster, Loan Growth and Disaster Recovery

The table presents results from the OLS regressions that test the effects of CCB loan growth after the disaster intensity on economic recovery. The sample consists of 605 city-year observations for our sample period from 2007 to 2017. We consider subsamples of cities based on the CCB loan growth after the disaster. In Columns 1 and 2, the dependent variable is the city lighting growth in year *t*+1. In Columns 3 and 4, the dependent variable is the city GDP growth rate in year *t*+1. *High* (*Low*) *CCB Loan Growth* is one if the CCB Loan Growth in year *t* is greater (lower) than the sample median and zero otherwise. *Disaster Intensity*$_{t-1}$ is the city-level disaster intensity in year *t*-1, measured as the total number of disasters with substantial economic impact. The detailed descriptions of other variables are available in the Appendix. *t*-statistics are reported in parentheses and are based on standard errors clustered by cities. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	City Lighting Growth$_{t+1}$		City GDP Growth$_{t+1}$	
	(1)	(2)	(3)	(4)
	High CCB Loan Growth	Low CCB Loan Growth	High CCB Loan Growth	Low CCB Loan Growth
Disaster Intensity	0.052**	-0.003	0.004**	0.004*
	(2.50)	(-0.15)	(2.19)	(1.89)
Log (City GDP)	-0.030	0.357	-0.122*	-0.279***
	(0.490)	(0.292)	(0.066)	(0.075)
City Budget Surplus	0.012	-0.192	-0.007	0.163***
	(0.060)	(0.181)	(0.014)	(0.047)
Size	-0.274**	-0.161**	-0.029	0.015
	(0.117)	(0.072)	(0.022)	(0.026)
Equity / Assets	-1.670**	2.103	-0.220*	-0.036
	(0.708)	(1.388)	(0.117)	(0.151)
Return on Assets	0.929	-2.529	-2.244**	-0.245
	(3.574)	(6.556)	(1.082)	(1.489)
Loan / Deposits	-0.723*	-0.324	-0.034	-0.010
	(0.412)	(0.375)	(0.065)	(0.063)
City Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	153	100	294	311
Adjusted R-squared	0.633	0.563	0.648	0.507

Appendix. Variable Definitions

- *Loan Growth* is the difference between total CCB loans in year *t* and year *t*-1 scaled by total loans in year *t*-1
- *Disaster Intensity* is the city-level disaster intensity in year *t*-1, measured as the total number of disasters with substantial economic impact.
- *City GDP* is the logarithm of the city GDP at year *t* in billion Yuan.
- *City Budget Surplus* is the difference between city j's fiscal revenue and expenditure at year *t* in billion Yuan.
- *Size* is the logarithm is total assets of the bank in billion Yuan.
- *Equity / Assets* is bank's total equity as a share of total assets
- *Return on Assets* is bank's net income as a share of total assets
- *Loan / Deposits* is bank's total loans as a share of total deposits
- *Corporate Loan Growth* is the difference between total CCB loans for corporate borrowers in year *t* and year *t*-1 scaled by corporate loans in year *t*-1.
- *Household Loan Growth* is the difference between total CCB loans for household borrowers in year *t* and year *t*-1 scaled by household loans in year *t*-1.
- *Non-Performing Loan ratio* (%) is the percentage of non-performing CCB loans in year *t*
- *City Lighting Growth* is the difference between city-level satellite night light data in year *t* and year *t*-1 scaled by city-level satellite night light data in year *t*-1.
- *City GDP Growth* is the difference between city-level GDP in year *t* and year *t*-1 scaled by city-level GDP in year *t*-1.