In the Eye of the Storm

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In the Eye of the Storm: Financial Intermediation in the Face of Natural Disasters

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A thesis submitted for the degree of
Doctor of Philosophy at Maastricht University

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In the Eye of the Storm: Financial Intermediation in the Face of Natural Disasters

DISSERTATION

to obtain the degree of Doctor at Maastricht University,
on the authority of Prof. dr. Rianne M. Letschert, Rector Magnificus,
in accordance with the decision of the Board of Deans,
to be defended in public
on **Friday, August 31, 2018**, at **12:00 hours**.

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Acknowledgements

The story happened in May 2100 in a tiny riverside village in the northwest low land of the Earth.

A young man, Konstantin, sitting under a poplar tree, opened the first page of a book. It was late spring, the most beautiful season and known to have the most hours of daylight. This land was scenic in all seasons, but only in May would the clouds have vacations and gave people more chance to enjoy the sun. The solar rays penetrated the light-green leaves of the young poplar tree, casting flecks on Konstantin. Even though not being born with a silver spoon and given high expectations by neighbors, time had by degrees bestowed him with handsomeness and charisma as he was kind to people and knew how to rein his temper.

As for the book, it was by no means worth mentioning, not only because it was thin with curved margin, but because Konstantin took it thoughtlessly. He just found a dusty book in the corner of an old table and wanted to kill ten minutes with it. More to his dismay, when he opened it, he found it was a dissertation, which did not make any sense for a boisterous youth to read. Once he decided to put it aside, he suddenly recollected a story told by his grandfather about this very humble brochure.

It was a long time ago when Konstantin's grandfather was a cheerful university student at an age no older than his grandson now. One day, he saw an announcement of a PhD defence.

"At that time, my kid, I was ambitious to become a scholar, to discover the truth of the universe, to guide people to a better life," said grandpa. He went into the defence hall in a solemn manner. He still remembered a feel like electricity running in his legs and a sincere appearance on his face. The exact contents of the defence was beyond the memory of that innocent student. What he was left with was a vague impression of the defender and this book.

"He was Chinese. His colleagues addressed him as hmm... Jack."

"After the defence, many books were carelessly left by people on the seats. I simply picked up one."

Another few words that Konstantin could recall from his grandfather's story were that he did think "a few sentences at the beginning of the book are inspiring."

The old man named Jack had deceased into obscurity many many years ago and Konstantin's grandpa also left him for a long time. Believing in his grandpa, the young man started to read. He was soon caught by it.

Following carefully the flow of ink, Konstantin had learnt that Jack had spent his early years as a junior scholar in the Netherlands. He was grateful to his parents for everything, including their decision to send him there. In the prelude, he praised the Dutch people for being hardworking and creative. He appreciated the country's people and their ancestors, including Spinoza, van Gogh, and Henk Sneevliet.

By Jack's narration, Konstantin traversed the fields and hills of St.Gerlach, picked an apple in the orchard in Gronsveld, cycled across the bridge in Eijdsen, breathed the tranquility in a deserted castle in the Saint Pietersberg. The most common yet touching element was the water. The Maas took away the everyday hustle and bustle in the downtown, the Albert Canal belonged to the industrial workers who dwelt at the margin yet provided materials to ensure the function of urban life, and on the Jeker rested the swan family and lay the serenity of the countryside.

Konstantin knew that Jack used to be encouraged when he, as a freshly graduated master student, read the following sentence in an essay written two centuries earlier:

“Rowan took the letter and did not ask, ‘Where is he at?’”

And though not fully achieved, he did occasionally entertain the wish to “carry a message to Garcia.” He had many “Garcia’s” at that time, two of whom stood out: Jack had two mentors to whom he was sincerely indebted.

One was Jaap Bos, an empathic and imaginative professor; another was Mark Sanders, a decisive scholar. “I could not become a qualified and happy PhD if I did not serve as Jaap’s research assistant and if I did not receive his help when I applied for a position. It usually takes me two or more years to understand one important suggestion from Jaap, which makes me blame myself but more thankful for his patience.” Jack continued to write, “I could not graduate with confidence without Mark’s guidance. The demanding suggestions a few months before submitting the thesis were like sharpening the blade of a sword.”

Konstantin found that Jack shared a life with many wonderful peers and colleagues. Aderajew brought back his sense of humor that he never lacked as a child but somehow lost in the course of growing up. Michael was a knowledgeable officemate and friend that could answer all his questions. He cycled and played table tennis with Luuk, was warmly welcomed by Juan, Matthijs, and Mike in events they organized, was brought to Stuttgart by Tobias and had the most memorable trip.

He met outstanding predecessors, Hang and Shusen, who generously shared

their experiences and charted the map for his future career, received kind help from like-minded people like Peiran, Stefan, Stefanie, and Pierre Mohnen, and learned teaching from Carl, Pomme, and Thomas. In the months before leaving, he was accompanied by younger colleagues like Joyce, Martijn, and Matteo.

Many organizations are led by their secretaries and Jack's finance department was no exception. People gathered closely around the four big S, Carina, Cécile, Els, and Francien, to form a family of common future.

Jack was blessed with a group of sibling-like Chinese peers who supported him in all aspects. Festivals with Ming, Yicong, and Fan, patriotic discussions with Young and Hongmao, and an excursion with Rui and Bihui. These moments were skillfully weaved together by life using her thread – time – that can be so fine as to escape the perception of everyone.

These details about Jack reminded Konstantin of a verse from *The Golden Rose* by Paustovsky. It said:

“Every minute, every chance word and glance, every thought – profound or flippant – the imperceptible beat of the human heart, and, by the same token, the fluff dropping from the poplar, the starlight gleaming in a pool – all are grains of gold dust. Over the years, we writers subconsciously collect millions of these tiny grains and keep them stored away until they form a mould out of which we shape our own particular golden rose – a story, novel, or poem. From these precious particles a stream of literature is born.”

As the narration continues, Konstantin knew people like Lidwien, Irene, Judy, Clarissa, Ehsan, Inka, Nora, Wiebke, Nagihan, Marc, Marina, Iman, and Alessandro. He was acquainted with Rachael, Rob, Sanne, Dennis, Jeroen, Nils, Joost, Paul, Paulo, and Peter. Everyone had glistening characteristics. Everyone's merits were carefully noted down by Jack.

In a salient position, Jack thanked his reading committee members, Piet Eichholtz, Olaf Sleijpen, Wouter Botzen, and Michael Koetter. Their time and effort in reading and evaluating the thesis were greatly acknowledged.

Konstantin could not meet anyone of these lovely people in person, but in the secular world, similar virtues possessed by them are found everywhere. These virtues are like water drops in Maas, in Albert, in Jeker, and in the sea. They form an infinity of shapes: ripples, waves, and floods. Some are clear, some are muddy, some are quiet, some are ardent, yet nothing lasts forever. The only immortality seems to lie in the reflective ability of water. Like the Maas: it has mirrored a melancholy tender lady leaning on the wooden bridge, reflected a young poet by

the bank chanting some ancient verse. It has witnessed soldiers departing from their parents to go to the battle fields in war times, and heard the joyful rumbles of vessels' engines when peace returned.

When Konstantin turned to the next page, he saw an old picture in which two youths were teasing. One with an enormous stature was rubbing the curly hair of a giggling black man. That the Spanish gentleman worked twelve hours everyday and that the black man became more clear-headed the more beer he drank were facts that had faded into the silent universe, left only Konstantin feeling that he was living at the present, a feeling, from which, however, he perceived happiness, power, and wisdom. With this state of mind, he understood, without having any emotions – fervent or poignant, that sometime in history, somewhere on our planet, there were a number of people: they met, created, celebrated, laughed, wept, sighed, and finally, bade farewell.

The acknowledgements of Jack influenced Konstantin, so he was determined to continue in the hope of having more excitement. However, the late spring sun was so warm that he felt sleepy after reading five more lines. He dropped the book and went into the house to have a nap. But the weather here was changeable and quickly there came a downpour. When Konstantin woke up, he found that the book was soaked through. He carefully tore pages off the book and put them on the stones to dry. In the next day, all pages were dry but most were stuck firmly on the stones and could not be removed without damage.

Fifty years later, Konstantin and his family left the village that was later turned into a resort. Most passages stuck on the stone were faded, except for a few sentences on the first few pages: they had endured the erosion from wind and rain. Another one hundred years later, the village was flooded by the sea. Now, no words can be found, no words are necessary. The vast sea and the still sunshine seem to tell that nothing has ever happened.

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Introduction

In May 2008, a devastating earthquake with a magnitude of 8 struck the southwest provinces of China. Immediately after the earthquake, all individuals, governmental organizations, and business sectors were mobilized to help victims recover from the disaster. Chinese banks, by offering timely credit assistance and easing up payment requirements, fostered the disaster mitigation. For example, the Industrial and Commercial Bank of China allowed credit cardholders in the affected area to apply for a deferral repayment and the late-payment fees were exempted.¹ In the United States, after Hurricane Irma in August 2017, bank regulators agreed to provide regulatory assistance to affected institutions subject to their supervision and encouraged institutions in the affected areas to meet the financial services needs of their communities.² On the contrary, the 2010 earthquake in Haiti caused about 100,000 deaths, more than the death toll of China in 2008. And after the quake, Haiti's recovery mainly relied on foreign aid.

These facts show that financial and political institutions play an important role in relieving natural disasters and in promoting recovery. Today, with climate change and the expansion of economic activity, natural disasters become more frequent (see Figure 1.1) and they impose greater threat to the safety of both individuals and countries. Understanding how financial and political institutions react to disasters and find a way improve their efficiencies are important for everyone who cares about the welfare of human beings.

This dissertation studies how institutions are affected by natural disasters and how they react to disasters. Utilizing disaster data from regional to world level and collecting economic data from specific institutions to macroeconomic variables, I explore three related issues. First, I use regional earthquake data to study the impact of disaster experiences on bank risk taking that is measured from the balance sheet and the lending style perspectives. Knowing how banks choose their business models based on their disaster experience is important because banks having had too many disastrous experiences can become more conservative, making them unwilling to engage in lending risky loans (Bouwman and Malmendier, 2015). Such behavior may hinder economic development by restricting access to credit for innovative but riskier industries. Further, understanding how banks change their

¹See "The Announcement for the Special and Favorable Services Offered for Peony Credit Cardholders in Sichuan Quake-affected Areas" on the ICBC website.

²See the press release on the website of the Federal Deposit Insurance Corporation (FDIC): <https://www.fdic.gov/news/news/press/2017/pr17069.html>.

Figure 1.1: Number of Worldwide Disasters by Year and Type. Data Source: Centre for Research on the Epidemiology of Disasters.

lending appetite after experiencing natural disasters is another important issue. This is because if banks become more likely to lend to credit-worthy borrowers, then the welfare of poorer people will be affected due to limited access to funds.

Next, I study how banks strategically allocate assets after natural disasters. It is well documented that disasters drive up the demand for loans (Chavaz, 2014; Cortés, 2017). How do banks satisfy such sudden increase in loan demand? I argue that banks make use of this increase in credit demand by charging higher interest rates for demanded loans and then issue more loans. To finance the loan origination, banks sell government bonds that are more liquid than loans but earn a lower interest. How should banks do if selling government securities still cannot meet the increased demand? I claim that when this happens, banks will first extend their lending to safer or more profitable loans and decrease other types of loans. Along with the geographical diversification strategy documented by Cortés and Strahan (2017), my study points out that banks can use the asset structure diversification strategy during disastrous times. In this way, banks not only guarantee a smooth shareholder value but also serve the community, which is a win-win solution.

Last but not least, I use worldwide disaster data to examine the role of governmental institutions in disaster relief. Natural disasters happen more frequently in recent years (Pachauri et al., 2014; Guha-Sapir et al., 2015). Providing timely assistance to victims and reducing disaster-induced losses are important goals for many countries. I claim that institutional quality, measured by government ef-

fectiveness, control of corruption, and regime stability, etc. plays a key role in reducing the death toll. Countries with better institutions have higher disaster-relief efficiencies, lower mortalities, but larger material damages. Developing countries such as China and India have experienced increased efficiencies since the last decades.

In the following three subsections, I will give more detailed descriptions regarding the backgrounds, motivations, and findings of the three chapters respectively.

1.1 Disaster Experiences and Bank Risk Taking

In Chapter 2, I study the long-run impact of natural disasters on banks' risk-taking behavior. I look at both the balance sheet structure and lending preference to characterize risk taking. Although there are abundant studies on the immediate response of banks to disasters, to our knowledge, this chapter is the first to examine the long-term impact. I argue that examining the long-run impact of disasters is important because of two reasons. First, we all agree that our lives are shaped by our mother nature. But how does nature shape financial institutions? As nature and disasters are important to our lives, we need to find an answer. Second, disaster experience is either a good or bad thing. For financial institutions, if their experiences lead them to be too prudential and even biased against people who are deemed to be less credit-worthy, then this is an inequality issue that calls for government intervention.

I focus on banks and earthquakes in California. The results confirm that banks that have had more intense earthquake experiences at the branch level as well as the headquarter level maintain a lower level of real estate loans, boost their equity buffer, and prefer high-income borrowers compared with banks having less intense experiences. Further, using deposit data at the branch level and demographic data at the county level, I find such changes are related to the evolution of local deposit supply. Particularly, more intense disaster experiences lead to decreases in both the deposit supply and the median household income. Last but not least, by showing that banks have longer memory for past events than individuals do, my paper implies that institutions are slow in adapting themselves to new situations, making it necessary for policy makers to stimulate institutions to better serve the society.

1.2 *Natural Disasters and Bank Asset Allocation*

In Chapter 3, I focus on how banks adjust their asset allocation in response to changes in loan demand and loan prices after natural disasters. Natural disasters destroy firms' capital and interrupt people's life. Disasters reduce capital stock, and consequently drive up credit demand as well as interest rate. How banks with limited funds satisfy this sudden increase in credit demand? What are the economic principles underlying banks' asset allocation?

I answer these questions through both empirical and theoretical analyses. In the empirical analysis, I find that the amounts of total loans and real estate loans significantly increase after natural disasters, while the holdings of commercial loans and government bonds decrease. This result is robust to different lengths of the event window and is consistent with previous findings that confirm residents increase their demand for mortgage loans and banks react to it by selling government securities (Cortés, 2017)

In the theoretical section, I develop a dynamic credit rationing model with multiple assets. In the model, natural disasters destroy firms' capital, leading to a surge in the demand for loans and an increase in the borrowing interest rate. The impact of disasters on banks are twofold. On the one hand, banks first suffer delayed or defaulted loan payment as disasters destroy firms' capital. On the other hand, banks have the opportunity to exploit the increased credit demand and interest rates. I therefore show that by strategically allocating assets, banks can benefit both themselves and the communities.

1.3 *Good Governance and Efficient Disaster Relief*

In Chapter 4, I use the stochastic frontier framework to evaluate and rank countries' disaster-relief efficiencies. I provide evidence that countries with better institutional quality on average have higher efficiencies. I show that, by reforming their institutions, countries, especially emerging ones, have increased their resilience in the last decade.

I first estimate efficiencies using the stochastic frontier model. The frontier is the minimum level of cost, measured by mortality, number of affected people, and material damage, that a country can achieve given factors such as its economic and natural preconditions and the intensity of the disaster. Conditional on those factors, a country is more efficient if its estimated cost is more close to the frontier. I detect that developed countries are more close to the frontier than developing nations.

I then show factors that can affect such differences in disaster-relief efficiency. I find that institutional variables, especially governance quality indicators, such as government effectiveness, control of corruption, regime durability, voice and accountability, and regulatory quality, promote the efficiency.

I next estimate the relationship between our estimated efficiencies and our three measures of cost. I show that higher efficiencies imply lower death toll and number of affect people but higher material damage. I thereby confirm the trade-off between the human mortality and the material damage.

In short, this dissertation studies how financial and political institutions react to natural disasters. I find that banks can better serve the communities' increased credit demand by strategically adjusting the balance sheet structure, and government can better handle disasters by imposing some monitoring effort on banks' lending style, and more importantly, by improving the quality of institutions. As more and more financial and technological innovations are applied to manage natural disaster risk, scholars should constantly evaluate their implications for the society.

Understanding the Trembles of Nature: How Do Disaster Experiences Shape Bank Risk Taking?

2.1 *Introduction*

Due to the expansion of population and climate change, natural disasters become more and more frequent. Disasters not only have a close relationship with local communities but also interact with banks. Banks lend funds to companies and households, thereby ideally promoting and sustaining firm productivity and enhancing customers' welfare. The extent to which banks can perform this role can be greatly affected by natural hazards. It is commonly known that natural disasters affect banks in two distinct ways (Collier, 2014; Koetter et al., 2016; Cortés and Strahan, 2017). On the one hand, natural disasters temporarily stimulate the demand for loans by destroying firms' productive capital and household property. On the other hand, natural disasters usually trigger defaults of existing loans and therefore may lead banks to become more cautious in issuing loans, resulting in an insufficient credit supply to support economic recovery.

There is ample evidence on how banks adjust their asset structures and lending activities after various types of natural disasters (Berg and Schrader, 2012; Chavaz, 2014; Collier et al., 2011; Cortés and Strahan, 2017; Klomp, 2014). However, most studies focus on the immediate response of banks to catastrophes and overlook the long-term impact of disaster experiences on banks' balance sheet structures and lending patterns.

In this paper, we argue that examining the long-run relationship between banks and natural disasters affords us with important additional insights on the effects of large shocks to the financial sector. A first insight relates to the long-run changes in the supply of banks' funds as a result of disaster experiences. For example, we know already that banks are sensitive to their exposure to real estate because real estate loans are particularly prone to defaults after a shock (Hott, 2011). But it is more interesting to know how banks adjust their real estate lending in the long run. Of course, banks that repeatedly experience disaster-related defaults tend to purposefully contract their real estate loans. But such a reduction in loans may also reflect changes in external market forces. Specifically, intense disaster experiences can lead to reallocation of economic activities from

This chapter is co-authored with Jaap Bos (Maastricht University).

one county to another, resulting in a long-run drop in either banks deposits or the demand for real estate loans. A short-run analysis cannot capture such a gradual demographic and economic evolution, which is why we need a long-term investigation.

A second insight relates to the resilience of banks to future shocks. After all, even if we know that banks with a higher equity buffer can better satisfy the disaster-driven increase in credit demand than banks with a lower equity level, we still need to establish whether such adeptness is the result of them having gradually learned from their hazard experiences, or whether each new shock triggers a reaction that is independent of previous disaster experiences. If banks have indeed become more prudent and then decide to keep a higher capital level after learning from their past disaster experiences, they will be more resilient to future disasters. We therefore study how long-run disaster experiences have shaped banks equity buffers.

A third and final insight relates to quality adjustments as a result of disaster experiences. In addition to reforming their balance sheet structure to enhance their resilience to future shocks, banks that have stronger disaster experiences may adjust their loan quality. Though theories have predicted that more capital enhances screening and monitoring and thus promotes the access to credit of poor borrowers (Holmstrom and Tirole, 1997; Mehran and Thakor, 2011), banks may still switch to high-income borrowers if disasters have increased the perceived riskiness of their loans to a great extent. Furthermore, by tightening the budget constraint, repeated disasters may worsen discrimination of ethnic minorities' loan applications if banks have a subjective bias against minorities. Motivated by these concerns, we study how long-run natural disaster experiences have affected banks' lending preferences.

These insights are closely related. Put simply, to protect themselves from losses, banks repeatedly experiencing disaster-related defaults may boost their capital level, reduce their exposure to risky real estate loans, and target borrowers with a better credit quality. Each of these attempts at reducing disaster risk exposure has its own distinct features. Except for the capitalization that largely captures the bank's own risk expectation, both real estate lending and borrower selection patterns are heavily determined by market forces. Specifically, by triggering the flow of migrants (Elliott, 2014), disasters change the residential composition of a region (e.g. income level, labor productivity, and race), alter the supply of deposits or the demand for loans, and resultantly affect the level of risky loans and lending patterns of banks. In this respect, our risk-taking measures weave together a general equilibrium story, which, to our knowledge, has not been fully

documented.

In this paper, we therefore answer three, related research questions. First, we examine whether banks having stronger disaster experiences maintain a lower level of real estate loans and a higher level of capital. Second, we study whether higher disaster exposure leads banks to prefer high-income borrowers and become more biased against ethnic minorities when extending loans. Third, in order to explore what makes long-run disaster experiences particularly salient for the decision making of banks and to address the long-run changes to banks' customer bases, we analyze the supply and demand sides of bank funds, that is, we investigate whether the local population around and deposits in bank branches have changed over the past years because of natural disasters.

To answer these related questions, we focus on banks (1994 to 2013) and earthquakes (1769 to 2013) in California. The reasons for choosing California are threefold. First, earthquakes are the dominant natural hazard in California, occurring with a relatively high frequency compared to other types of disasters.² Second, since earthquakes happen frequently and have received much attention from research institutes and the state government, historical earthquake records are abundant and easy to retrieve. Third, the California state government provides exemplary access to various economic and demographic data, e.g. unemployment rate, population, and household income. Such comprehensiveness of the data allows us to robustly identify the effect of the earthquake experience.

Our results confirm that long-run experiences do affect banks' risk attitudes and resilience to future shocks by altering the balance sheet structure and loan quality. Specifically, we find that banks that have had more intense earthquake experiences maintain a lower level of real estate loans, boost their equity buffer, and prefer high-income borrowers compared with banks having less intense experiences. For example, an increase in the earthquake experience from its 10th percentile to its 90th percentile is associated with a decrease in the proportion of real estate loan to total assets of 3.1 percent and a decrease in interest income of 4.9 percent. Further, using deposit data at the branch level and demographic data at the county level, we find such changes are related to the evolution of local deposit supply. Particularly, more intense disaster experiences lead to decreases in both the deposit supply and the median household income. Last but not least, we find that banks whose earthquake experiences are in the bottom decile tend to increase their real estate lending and reduce their equity level, indicating that

²Another major type of disaster in California is wildfire. But unlike earthquakes that can hit both the residential and non-residential areas, wildfires mainly occur in non-residential regions and thus have little effect on banks.

banks continuously surviving from smaller disasters may become more risk-loving. Thought, the effect of experience is significant even after controlling for geographic diversification.

This study connects to three strands of literature. First, the literature on macroeconomic experiences and individuals' risk taking shows that investors who have experienced high stock market returns are more willing to take risks (Malmendier and Nagel, 2011), and that banks that have undergone difficult economic periods tend to maintain a higher capital level and are more prudential in issuing loans (Bouwman and Malmendier, 2015). Based on an episode of financial distress in 1772 in Amsterdam, Koudijs and Voth (2016) find that lenders' personal willingness to take risks declined after the incidence even if they did not suffer from individual losses. We contribute to this literature by showing that, besides economic factors, natural hazards can also affect banks' risk attitudes and alter their asset structure in the long run. A more related study is by Berger and Udell (2004) who apply the institutional memory hypothesis to explain the procyclicality of bank lending. They find that credit standards ease as time passes because loan officers tend to gradually forget the last bank crisis. We differ from their paper by showing exactly another aspect of memory, that is, the long-lasting property of disaster memory. We also argue that such long-lasting memory exists both in banks and in local residents.

Second, this paper complements the currently popular literature on the relationship between natural disasters and bank lending (Berg and Schrader, 2012; Chavaz, 2014; Collier et al., 2011; Cortés and Strahan, 2017). Using earthquake risk data and commercial real estate transaction data, Garmaise and Moskowitz (2009) find that inefficiencies in the catastrophe insurance market reduce the provision of bank credit, limit the market participation of less wealthy investors, and hamper neighborhood revitalization in disadvantaged areas. In a case study of the 1994 Northridge earthquake in California, the authors document a reduction in bank lending to high risk properties but find no significant longer-term effects arising from the Northridge earthquake. Our study differs from these papers by focusing on the long-term disaster experience. Particularly, by verifying that banks adjust their balance sheet structure according to their experiences, we show that the response of a bank to a new disaster depends on its own disaster history. Further, our results confirm that early earthquakes do not easily fade away from the memory of banks and thus significantly influence banks' current financial decisions.

Third, by investigating the channels making disaster experiences crucial for banks, our paper connects to the financing growth literature (King and Levine,

1993; Levine, 1997; Pagano, 1993). Importantly, we show that communities also learn from earthquake experiences, leading to changes in their population and income structures throughout the history. Such evolution is responsible for changes in the business practices of banks. To sum up, to the best of our knowledge, this study is the first to link the balance sheet structure and loan quality of banks to their long-term natural disaster experiences.

The paper proceeds as follows. Section 2.2 explains the empirical method and identification strategy. Section 2.3 introduces the data, visualizes earthquakes, and summarizes key statistics. Section 2.4 presents and interprets our empirical results, explores changes in market forces associated with disaster experiences, and discusses robustness checks. Section 2.5 concludes.

2.2 Estimation Method and Identification Strategy

To analyze the relationship between earthquake experiences and the risk taking of banks measured from the perspective of balance sheet structure (real estate lending ratio and capital ratio) and lending practice (borrower income and ethnicity), we primarily rely on the following generic regression model:

$$y_{it} = \alpha + \beta E_{it}(\lambda) + \gamma' x_{it} + \epsilon_{it}, \quad (2.1)$$

where y_{it} is one of our four risk-taking measures of bank i at time t , E_{it} is the earthquake experience of the bank, λ is the shape parameter that determines the slope of the weighting scheme, and x_{it} is a vector of control variables that includes bank characteristics (total assets, ROA, imputed interest rates, bank age, number of branches, and proportion of branches in less hazardous counties) and regional demographics (poverty rate, population, and unemployment rate).

For each branch, the shape parameter λ determines the slope of the weighting function. A positive λ leads to a downward-sloping curve, meaning that the branch gradually forgets early earthquakes and attach bigger weights to recent earthquakes. A negative λ indicates an upward-sloping curve, meaning that early earthquakes have left vivid impression to the branch. If λ is zero, then the branch weighs all earthquakes equally.

As shown in equation (2.2) and (2.3), $E_{it}(\lambda)$ is constructed as a nonlinear function of the unknown parameter λ . Thus to estimate β and λ simultaneously, nonlinear estimation methods are needed. However, as the number of bank branches in our sample is huge and the unit of our earthquake weight (w_{bk}) is

daily, nonlinear methods prove to be exceedingly time-consuming. To improve efficiency, we therefore first estimate the equation on a tightly spaced grid of values for λ (step=0.02) and then use the λ and the estimates that lead to the lowest residual sum of squares as our final estimated coefficients.³ In this way, we effectively transform a nonlinear regression to several linear regressions by fixing the value of λ in every regression.⁴

Despite the exogenous nature of earthquakes, our study still faces a few identification issues.⁵ The first one is that earthquakes are not uniformly distributed within California. As shown in Figure 2.1, even though earthquakes are prevalent, a few counties in the middle region (especially the northern part of the *Great Valley*) have significantly less earthquakes than other counties. If banks deliberately choose to open more branches in this “*NonHaz*” *Region* (i.e. the region less prone to earthquakes, as will be defined in the Data section), then we cannot judge whether the current balance sheet structure and lending pattern are shaped by this geographical diversification strategy or by the earthquake experiences of banks. By plotting the distribution of bank branches in Figure 2.2, we can already see that a considerable number of branches are located in the “*NonHaz*” *Region*, so banks may have already considered the earthquake hazards when locating their branches. To account for this confounding factor, we calculate for each bank the portion of branches in less hazardous counties and include this variable into our regression.

Another identification issue is related to outliers of earthquake experiences. In our sample, a few big banks have accumulated high values of experiences because they are old and have a large number of branches. We account for this issue by excluding the top 1% largest banks and by dropping extreme values of earthquake experiences ($E_{it} \geq 100$). We further control for bank ages and the number of branches of banks in our regressions. To control for the unobserved effect of the headquarter bank, we include dummies of counties where the headquarters are located. Finally, we use year dummies to absorb any unobservable aggregate macroeconomic factors that may affect bank risk taking.

In the next section, we explain how we construct our key variables and sum-

³To put it more in detail, we first try values of λ 's with a step of 0.5. After finding the best value, i.e. the value that yields the lowest residual sum of squares, we try values ± 0.5 around this best value with a step of 0.02 to pin down our final estimates of λ and other coefficients.

⁴This estimation method sacrifices the precision of λ , but reduces the running time of each of our regression programs from more than seven days to less than seven hours.

⁵It is worth mentioning that a remarkable advantage of studying the effects of earthquakes is the absence of reverse causality. In our case, the risk taking of banks can hardly be thought to cause earthquakes.

Figure 2.1: Earthquake Distribution for California (2006-2010). This map plots geographical locations of earthquakes of California for the period 2006-2010. Marker size and color darkness are both strictly increasing in earthquake magnitude (min = 2.5, max = 6.5). The map shows 4818 earthquake events during this period. The data are obtained from the Search Earthquake Catalog of USGS.

marize statistics.

2.3 Data, Variables, and Descriptive Statistics

We use data from a variety of sources to construct our variables of interest. The key dependent variables are measures of risk taking while the chief explanatory variable is the earthquake experience.

2.3.1 Measures of Risk Taking

Our measures of risk taking can be classified into two categories. The first set of measures is based on the balance sheet structure of banks. Following the common practice, we use capital ratios and the share of risky loans to measure risk taking. The second set of measures is based on banks' lending inclination. Specifically, we examine whether banks tend to be biased toward different types of borrowers in

Figure 2.2: Bank Branch Distribution for California (2010). This map shows the distribution of branch offices of California banks by the date June 30, 2010. Marker size and color darkness are both strictly increasing in bank age (oldest: established on January 1, 1864; youngest: established on June 30, 2010). The data source is the Branch Office Deposits data of FDIC.

terms of their income and race.⁶

Measures Based on Balance Sheet Structure

We construct the capital ratio and the real estate lending ratio with balance sheet information from the quarterly Consolidated Reports of Condition and Income (Call Reports) for all commercial banks of California over the period 1994Q1 to 2013Q4.⁷ The Call Reports are collected at the bank level. However, since a

⁶In this paper, for simplicity we often count among our dependent variables as risk-taking measures. However, except for the capital ratio that is a pure risk-taking measure, all other variables reflect to some extent external market conditions. For instance, real estate loans are partly determined by the supply and demand of funds by consumers and industries and are not fully decided by banks on their own. In fact, exploring the “market forces” channel constitutes an important part of this study and distinguishes our paper from those on individuals’ lifetime experiences.

⁷This does not mean, however, that we only have 20 years of records of earthquakes. In fact, since the experience variable is constructed based on bank branches, some of which were established circa 1850, we use the earthquake data from the early 19th century to the present.

bank’s disaster experience is an aggregate of its branch-level experiences, we later match branches to their headquarters using bank identifiers.

The level of risky loans is a crucial measure of bank risk taking. Among all types of loans, real estate lending accounts for the biggest part of total lending (about 50 percent; see Table 2.1 for descriptive statistics) and is an important source of income for commercial banks. Meanwhile, real estate loans have been recognized as the main culprit of bank failures during the global financial crisis (Cole and White, 2012). Earthquakes can impose tremendous damage to buildings relative to other kinds of natural disasters. We therefore use the real estate lending ratio, defined as *real estate loans/total assets*, as a risk-taking measure.

The capital ratio is a commonly used variable in the literature to characterize the willingness of a bank to take risks (Berger and Bouwman, 2013; Schwer et al., 2018; Thakor, 2014). It measures a bank’s amount of equity relative to its total assets. Banks with higher capital ratios have a greater capability of surviving adverse financial conditions (Berger and Bouwman, 2013), while banks with lower capital ratios are more prone to defaults that can be pronounced during natural disaster periods (Collier, 2014). We therefore use the capital ratio as a risk-taking measure. Specifically, in line with Berger and Bouwman (2013), we define the capital ratio as the ratio of total equity to GTA, where GTA is total assets plus the allowance for loan and lease losses and the allocated transfer risk reserve.⁸

Measures Based on Lending Preferences

In this study, we go a step further by measuring risk taking from banks’ lending preferences. A conservative bank expecting a higher default probability of its loans may carefully evaluate borrowers and choose to lend to those who are able to repay loans in time. In the light of this statement, we construct a borrower income measure and a borrower race measure from the Home Mortgage Disclosure Act (HMDA) data for all California commercial banks over the period 2010 to 2013. The HMDA database contains public loan data for various types of lending institutions, including banks, saving associations, credit unions, and other mortgage lending institutions. A lending institution, say, a branch of a bank, needs to report all loan transactions for a whole calendar year. Each transaction record contains up to 45 variables, including the institution’s ID, loan amount, borrower’s income, and the borrower’s race.

These two measures are at the year-bank level. The borrower income measure

⁸The equity ratio is frequently referred to as “equity ratio”, “equity capital ratio”, or “capitalization”. It is also commonly represented by the Tier 1 risk-based capital ratio defined by Basel III report in many studies (Schwer et al., 2018; Dell’Ariccia et al., 2016).

is constructed as follows. For each year, we calculate a bank’s mean borrower incomes by taking the average of all branch-level borrower income. As income is positively related to credit quality, we posit that a bank may prefer to lend to high-income borrowers if stronger earthquake experiences have led the bank to become more risk-averse.

The borrower race measure is defined as the proportion of a bank’s nonwhite borrowers in a given year. Specifically, for every bank, we calculate the ratio of the number of nonwhite borrowers (denoted by 1 to 4 in the “Applicant Race 1” entry) to the number of all borrowers. Since one of the purposes of the HMDA data is to identify possible discriminatory lending patterns, we explore whether lending discrimination can be driven by natural disasters that impose funding constraints on banks.

2.3.2 *Explanatory Variables*

The Earthquake Experience

The key explanatory variable in this study is the earthquake experience. Intuitively, it has a straightforward meaning as the measure of how strongly a bank has been affected by earthquakes, which are largely exogenous, during its operating history. One concern is the endogeneity problem that can arise if banks deliberately choose to open branches in less riskier regions. We tackle this important issue in detail in Section 2.2.

To construct the earthquake experience variable, we use bank branch data and earthquake data. The branch data are from the Summary of Deposits (SOD) of the FDIC. The SOD is a publicly available annual survey that reports branch-level deposits for all FDIC-insured institutions. Aside from the deposit data, the SOD also records the geographic coordinates, county, and date of establishment for each branch. The headquarter bank of each branch is identified by the FDIC Certificate Number. The data reveal that the history of Californian banks can be dated back to the middle of the nineteenth century. For example, the Bank of Stockton, one of the oldest banks in California, was established on August 12, 1867. To account for earthquake experiences of old banks, we therefore need a long list of historical earthquakes.

Fortunately, earthquake data for California are available and complete. We compile earthquake data from two major sources. The first source is the geological survey by Stover and Coffman (1993) in PDF format that covers the earthquakes of California from 1769 to 1989. The second source is the Search Earthquake Catalog of the United States Geological Survey (USGS). It is a digital database that

contains more comprehensive earthquake records since 1932. Before 1932, however, the USGS records are sparse. To form our earthquake dataset, we therefore manually take the records of Stover and Coffman (1993) from 1769 to 1931 and combine them with the USGS records from 1932 to 2013. The four variables we use to characterize each earthquake are the time of occurrence, latitude, longitude, and the magnitude. To illustrate the geographical dispersion of this type of natural disaster, we plot all earthquakes in California from 2006-2010 in Figure 2.1. The figure confirms that earthquakes are indeed a prevalent natural disaster in California: events occur nearly all over the state, including the economically developed costal regions. However, there are also a few counties in the middle part of California (the *Great Valley*) that apparently have few earthquakes. We define this region as the “*NonHaz*” *Region* and, in our empirical analysis, we use bank branches in this region to account for possible effects of geographic diversification on the balance sheet structures and lending practices of banks.⁹

We first use the method developed by Malmendier and Nagel (2011) and construct the earthquake experience for each branch b at date t as a weighted average of its past earthquake magnitudes. As shown in equation (2.2), the weighting scheme is determined by the age of the branch at time t (age_{it}), the date of the earthquake ($date_{t-k}$), the date of establishment ($estdate_b$), how long ago the earthquake took place (k), and a shaping parameter λ .¹⁰ A decreasing weighting function ($\lambda > 0$) reflects that early earthquake experiences fade away from the memory of the branch. An increasing weighting function ($\lambda < 0$), on the contrary, means that early earthquake experiences can have greater influence on a bank’s current decision-making than recent ones. In our empirical application, the estimated λ is the average value for the banks in our sample.

M_{t-k} denotes the earthquake magnitude. We let $M_{t-k} = 0$ when the magnitude of the earthquake on $date_{t-k}$ is less than 4, or when there was no earthquake; as a result, the branch’s earthquake experience on that day is zero.¹¹ We also ex-

⁹One plausible explanation that the Great Valley region (especially its northern part) has fewer earthquakes than the costal area is that it is relatively far away from the San Andreas Fault, a continental transform fault that extends roughly 1,200 kilometers through California along the east coast.

¹⁰The term $date_{t-k} - estdate_b$ represents how recent the earthquake is. A smaller value indicates an early earthquake that happened shortly after the date of establishment; a larger value means that the earthquake happened recently.

¹¹Choosing the threshold of 4 implies that banks simply ignore weaker earthquakes. The threshold is based on the effects of earthquakes described on the USGS website (https://earthquake.usgs.gov/learn/topics/mag_vs_int.php). According to the description, earthquakes with magnitudes between 3.0 and 3.9 are felt quite noticeably by persons indoors, especially on upper floors of buildings. But many people do not recognize it as an earthquake. In

clude earthquakes happening just one quarter before the current date t (i.e., we let k start at 90) to prevent any short-term effects of earthquakes on asset structures and to ensure that banks really behave according to their long-term earthquake experiences:

$$E_{bt} = \sum_{k=90}^{age_{bt}-1} w_{bk}(\lambda) M_{t-k}, \quad (2.2)$$

where

$$w_{bk}(\lambda) = \frac{(date_{t-k} - estdate_b)^\lambda}{\sum_{k=90}^{age_{bt}-1} (age_{bt} - k)^\lambda}.$$

Whereas Malmendier and Nagel (2011) focus on an individual investor, the banks in this study have multiple branches operating in different regions, and the earthquake experiences of branches thus differ from each other. In view of this feature, a bank's earthquake experience should eventually be an aggregate of the experiences of its branches. We construct the bank-level earthquake experience by using a set of deposit weights. In particular, as shown in equation (2.3), each branch b at time t takes a weight equal to the proportion of its deposit in the total deposits of all branches.¹² The underlying assumption is that if a branch has a higher level of deposits, its headquarter bank consequently attaches greater importance to its experiences when making financial decisions. The deposit weight ω_{bt} changes yearly because the deposit data are reported yearly. Finally, a bank's earthquake experience is the weighted average of branch experiences:

$$E_{it} = \sum_{b=1}^{B_{it}} \omega_{bt} E_{bt}, \quad (2.3)$$

where

$$\omega_{bt} = \frac{deposit_{bt}}{\sum_{b=1}^{B_{it}} deposit_{bt}}.$$

Aggregating experiences from the branch level to the bank level changes our interpretation of the shape parameter λ slightly. At the branch level, λ indicates

addition, earthquakes with magnitudes between 4.0 and 4.9 are felt indoors by many, outdoors by few during the day. At night, some awakened. Dishes, windows, doors disturbed; walls make cracking sound. Sensation like heavy truck struck building. Standing motorcars rocked noticeably. In our robustness checks, to further alleviate the concern about the ad hoc threshold, we vary the threshold magnitude. The major inferences nevertheless hold.

¹²Strictly speaking, the branch notation b should have a subscript i to denote that the branch belongs to bank i . We slightly abuse the notation to simplify our explanation, as long as the readers can understand.

how does each branch memorize its past earthquakes. For example, a positive λ means that early earthquake experiences fade away in the memory of the branch, and the higher the value is, the faster the experiences grow faint. At the bank level, however, λ is the average shape parameter of all the branches and to a certain degree can be interpreted as the memorizing pattern of the headquarter bank.

Besides the aggregation process, another feature in our variable construction is that the earthquake weight w_{bk} changes daily. Thanks to the data precision, we obtain the exact dates for each earthquake and branch establishment, while the filing times of the Call Reports and HMDA records can be set to the last day of each quarter or year. Specifying w_{bk} on a daily basis improves the precision of the experience variable and generates more variation within a quarter. The small cost is an increased calculation time. For example, we need to calculate nearly 3,650 weights for a branch established 10 years ago.

Bank Variables

We use Call Reports and the SOD data to construct the following bank-specific variables. *Total assets* measures bank size. *ROA* (net interest income/total assets of last quarter) indicates, given the capital base, how profitable a bank can be. *Imputed Interest rate* measures the cost of borrowing (for total loans, it equals total interest income/total loans and leases; analogously, for real estate loans, it equals interest income on loans secured by real estate/loans secured by real estate). *NonHaz branch%* measures the proportion of branches of a bank in counties that are less prone to earthquakes. Specifically, we manually outline counties of the “NonHaz” Region and divide the number of branches of a bank in this region by its total number of branches. *Bank age* is defined as the difference between the date of observation and the date of establishment of a bank.

Regional Variables

We include county-level economic and demographic variables. These variables serve two major purposes. In the first part of our analysis, they are treated as controls to account for the possibility that local conditions affect bank risk taking. In the second part, we use them as dependent variables to explore how a county’s current income level and residential composition have been shaped by its historical disaster experiences. We collect the median household income and poverty rate from the Census Bureau, the unemployment rate from the website of Employment Development Department of California, and the population and migration data from the website of the Department of Finance of the state of California.

2.3.3 Summary Statistics

Table 2.1 reports summary statistics for our main variables. Panel A reports the statistics for the full sample. However, to avoid the possibility that big banks can distort the picture, Panel B restricts the sample to banks that have less than or equal to 3 branches. Here, the median of the number of branches is three.

Table 2.1: Key Statistics

This table summarizes descriptive statistics for the variables used in our baseline regressions. The sample includes our four measures of bank risk taking. The capital ratio and real estate loan ratio are based on Call Report data from 1994Q1 to 2013Q4. They measure risk taking from the perspective of balance sheet structure. The borrower income and borrower race are based on HMDA data from 2010 to 2013. They measure risk taking from the aspect of bank lending preference. Branch deposit and branch number are from the Summary of Deposits of FDIC. NonHaz branch% indicates the proportion of branches of a bank in counties less prone to earthquakes. Bank age is the age of the headquarter bank. Poverty data are from the U.S. Census Bureau. Unemployment rate and population are from websites of the California government. Panel A includes data for all banks. To exclude the effects of big banks, Panel B restricts the sample to banks with less than or equal to 3 branches.

	Average	Standard Deviation	10 th Percentile	90 th Percentile	Observations
Panel A: Full Sample					
Capital ratio	0.124	0.077	0.074	0.185	12178
Tier 1 capital ratio	0.077	0.138	0.001	0.189	10608
Real estate loan ratio	0.477	0.176	0.256	0.700	13185
Borrower income (\$ thousands)	320.688	379.76	90	705.63	307
Borrower race%	0.218	0.325	0	0.903	307
Total assets (\$ billions)	4.155	45.602	0.068	2.303	13185
ROA	0.025	0.014	0.010	0.043	13185
Imputed Rate Total	0.058	0.045	0.019	0.099	13185
ImputedInt Rate RE Loan	0.044	0.024	0.016	0.074	13185
Deposit (\$ millions)	72.044	338.996	17.567	110.597	5181
Bank age (years)	24.119	27.787	2.751	48.712	13185
NonHaz branch%	0.092	0.260	0	0.363	13030
Branch number	18.434	87.433	1	21	13030
Panel B: Banks with Branch Number ≤ 3					
Capital ratio	0.142	0.095	0.078	0.226	5876
Tier 1 capital ratio	0.083	0.149	0.001	0.213	5747
Real estate loan ratio	0.480	0.182	0.245	0.703	6100
Borrower income (\$ thousands)	376.638	443.424	84	893.833	139
Borrower race%	0.190	0.328	0	0.9	139
Total assets (\$ billions)	0.322	1.657	0.050	0.365	6100
ROA	0.024	0.013	0.009	0.041	6100
Imputed Rate Total	0.058	0.050	0.019	0.095	6100
ImputedInt Rate RE Loan	0.042	0.024	0.016	0.069	6100
Deposit (\$ millions)	78.524	444.127	15.705	120.835	2748
Bank age (years)	11.620	14.436	1.584	26.742	6100
NonHaz branch%	0.076	0.260	0	0	6100
Branch number	1.815	0.799	1	3	6100

Comparing Panels A and B, we see that smaller banks tend to be younger than the average bank, with a mean age of 11.6 years rather than 24.1 years. The comparison also reveals that smaller banks are safer than the average bank as they

maintain a higher capital buffer, attract more deposits per branch, and lend to customers with a higher income. The patterns are similar for real estate lending ratio, ROA and interest rates.¹³ In our analyses, we control for total assets and the number of branches of every bank so the effect of earthquake experiences is not confounded by bank size.

Real estate loans comprise the biggest part of banks' balance sheets, averaging 47.7% of total assets, with a large standard deviation of 0.176. This suggests that real estate loans are an appropriate candidate to measure of the riskiness of the overall portfolio of banks. Furthermore, the average interest rate on real estate loans is 4.4% and has a small variation across banks and over time. On the contrary, the average interest rate on all loans is 5.8%, which is higher than the interest rate on real estate loans, indicating that banks possess a diversified loan portfolio with many assets more riskier than real estate loans.

2.4 Results

In this section, we start by presenting our main results on the effects of earthquake experiences on bank risk taking. We find that banks with intense earthquake experiences adapt their balance sheet structure to make themselves more resilient to defaults. Meanwhile, these banks are significantly more prudent in their lending practices. We next explore the channel linking earthquake experiences to bank risk taking and show that both market forces as well as the variations in banks' own risk perceptions drive the risk-taking patterns. We conclude with a battery of robustness tests showing that the main results remain intact when increasing or decreasing the sample size.

2.4.1 Balance Sheet Structure

Real Estate Lending Ratio

We start by linking the earthquake experience to the real estate lending ratio, defined as the ratio of loans secured by real estate to total assets. We choose the real estate lending ratio as an important measure of bank risk taking because real estate loans account for the largest part of total loans and are crucial for the financial stability of banks. Buildings are the most important collateral for loans. As earthquakes can cause tremendous damage to buildings, the real estate lending ratio measure is therefore especially relevant to our study.

¹³The above conclusions are based on formal t-tests between banks with more than 3 branches and banks with less than or equal to 3 branches.

The effect of earthquake experiences on the real estate lending ratio, however, is not obvious at first glance. As explained before, on the one hand, by causing damages to buildings, earthquakes not only trigger defaults of bank loans but also decrease the value of collateral. Banks that repeatedly suffer from defaults can learn from such experiences and subsequently reduce the issuance of real estate loans. On the other hand, earthquakes create investment opportunities in the future, and therefore possibly increase the demand for bank loans. Moreover, real estate loans may be affected by market conditions. For instance, residents with strong earthquake experiences may leave high-risk counties, causing decreases in both supply and demand of funds. Such market forces are explored in the next subsection. Here it suffices to know the overall effect of earthquake experiences on the real estate lending ratio.

The estimate of -0.219 for the coefficient β in column (iii) of Table 2.2 indicates a significantly negative relationship between earthquake experiences and the real estate lending ratio. To be more specific, the results imply that an increase in the earthquake experience from its 10th percentile to its 90th percentile is associated with a decrease in real estate lending ratio of 3.1 percent and a decrease in interest income of 4.9 percent.¹⁴ This differential effect is economically moderate given the large proportion of real estate loans in total assets (44 percent). However, since the results also reflect the opposite “rebuilding” effect, the actual “experience” effect can be big. In addition, as shown in Figure 2.1, earthquakes are quite evenly distributed across California, so the distribution of experiences is relatively concentrated. For the whole world, natural disasters are not evenly distributed; therefore the “experience” effect can play a significant role. Furthermore, if the disaster experience increases from its minimum to its maximum, the decrease in the real estate lending ratio is about 46 percent. This huge difference convincingly underlines the non-negligible effects of disaster experiences.

The value of 0.18 for the shape parameter λ corresponds to a weighting curve that is almost flat. It means that although banks attach more weight to recent earthquakes, old experiences do not easily fade away from their memory. Compared with the values estimated by Malmendier and Nagel (2011, 2015) for individuals’ experiences on stock returns and inflation, the value in our study is quite low. This indicates that institutions do not quickly forget past experiences and may respond less promptly to recent experiences than individuals do.¹⁵

¹⁴We evaluate this differential effect (i.e. the difference between the fitted real estate lending ratios at the 10th and 90th percentiles of the earthquake experience) at the sample means of the data. The results are the same if we evaluate the differential effects at every observation and obtain the sample average of the individual differential effects.

¹⁵Though Berger and Udell (2004) did not formally estimate a memorizing curve, they argue

Table 2.2: Disaster Experiences Decrease Banks' Exposure to Real Estate

This table reports regression estimates of real estate lending ratios from 1994Q1 to 2013Q4 on earthquake experiences of banks and a variety of banking and regional variables (poverty percent, population, and unemployment rate). The real estate lending ratio is based on Call Reports and is defined as the proportion of a bank's real estate loan to its total assets. The regional variables control for the macroeconomic and demographic conditions of counties that can affect the demand for real estate loans. The poverty percent, population, and unemployment rate are from the U.S. Census Bureau, the Employment Development Department of California, and the Department of Finance of California respectively. We estimate the model on a tightly spaced grid of values of the weighting parameter λ (step=0.02), and select the estimates resulting in the lowest residual sum of squares to be the final estimated coefficients. The standard errors robust to heteroscedasticity are reported in parentheses. The weighting parameters are shown in the first row. All the regressions control for year fixed effects.

	(i)	(ii)	(iii)
Weighting parameter λ	0.26	0.18	0.18
Earthquake experience coefficient β	-0.219 (0.017)	-0.218 (0.017)	-0.219 (0.017)
NonHaz branch%		-0.110 (0.020)	-0.107 (0.020)
Branch number			1.017×10^{-5} (2.028×10^{-5})
Bank-level controls	Yes	Yes	Yes
Regional controls	Yes	Yes	Yes
Headquarter fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Average of actual value at 90 th pct. minus actual value at 10 th pct. of earthquake experience	-0.031	-0.031	-0.031
Average of fitted value at maximum minus fitted value at minimum of earthquake experience	-0.461	-0.458	-0.461
R-squared	0.481	0.476	0.474
Observations	10625	10597	10545
Number of banks	415	415	415

We have included various bank-specific variables in the regression model. Among them, the *NonHaz branch%* is of identification importance because it measures how the geographic diversification strategy affects the balance sheet structure. Our results demonstrate that banks having more branches in disaster-prone counties maintain less real estate loans. This is not surprising given that – as will be explained later – the demands for real estate loans in these counties are low.

that bank managers forget the past crises quickly. As we are focusing on a very long time period (almost 200 years) and a different type of crisis (natural hazards), our results are not directly comparable to theirs.

Capital Ratio

Unlike the real estate lending ratio that is partially affected by the supply and demand forces of the market, a bank's capital ratio is mainly determined by the bank itself and is therefore a more direct risk-taking measure commonly used in the literature (Thakor, 2014; Bouwman and Malmendier, 2015). In a study on a microfinance institution in Peru, Collier (2014) found that the lender increased its capital ratio during the 1998 El Niño to endure disaster-related default risk. In line with this reasoning, in order to protect them from default risks, banks that frequently suffer from disasters may continuously keep a higher capital ratio than banks that have experienced fewer disasters. To test this hypothesis, Table 2.3 presents regression results of the effect of earthquake experiences on the capital ratios of banks in California.

The capital ratio is significantly negatively related to the earthquake experience, which means banks with stronger earthquake experiences eventually become more cautious than banks with fewer experiences. Specifically, going from the 10th to the 90th percentile of experiences in column (i) implies, on average, an increase in the capital ratio of 0.2 percent, or equivalently, 265 thousand dollars. The economic magnitude of this differential effect, however, is small compared to the standard deviation for the capital ratio of 11.2 percent.¹⁶ The results do not change after adding additional explanatory variables.

Besides using additional capital to absorb losses induced by defaults, banks can manage their default risks *ex ante*. Banks with more capital might be able to engage in more costly screening and monitoring activities (Holmstrom and Tirole, 1997; Mehran and Thakor, 2011) and therefore are more likely to lend funds to low-income borrowers. Does the increased equity help banks to lend more to low-income residents? Or, do banks switch to high-income borrowers so as to better endure losses rendered by the upcoming disasters? To explore this issue, we look at the lending preferences of banks in the next subsection.

¹⁶The current analysis does not consider the heterogeneity in experiences. However, in subsection 2.4.5, we find banks at the bottom decile of the earthquake experience reduce their capital ratio significantly, with a differential effect of -1.1 percent. Meanwhile, the standard deviation of the capital ratio is 2.8 percent. This finding implies that having very low earthquake exposure can significantly increase a bank's risk taking.

Table 2.3: Disaster Experiences Boost Banks' Capital Adequacy

This table reports results of estimating regressions of bank capital ratios from 1994Q1 to 2013Q4 on earthquake experiences and a variety of bank-specific variables (total assets, ROA, imputed interest rate, real estate loan, portion of branches in less hazardous regions, number of branches, and bank age). The dependent variable, capital ratio, is based on Call Reports. It equals the ratio of total equity to GTA, where GTA is total assets plus the allowance for loan and lease losses plus the allocated transfer risk reserve. Data for bank branches are from the SOD dataset of FDIC. To construct the earthquake experience variable for each bank, we match the earthquakes and bank branches by their counties of occurrence/location and then aggregate branch-level experiences to bank-level experiences based on the deposit amounts of branches. All other bank variables are from the Call Reports. All other variables are as defined in Table 2.2. We estimate the model on a tightly spaced grid of values of the weighting parameter λ (step=0.02), and select the estimates resulting in the lowest residual sum of squares to be the final estimated coefficients. The standard errors robust to heteroscedasticity are reported in parentheses. The weighting parameters are shown in the first row. The *NonHaz branch%* and *Branch number* are of identification importance and are thus tabulated explicitly. All the regressions control for year fixed effects.

	(i)	(ii)	(iii)
Weighting parameter λ	0.24	0.30	0.28
Earthquake experience coefficient β	0.008 (0.001)	0.006 (0.001)	0.007 (0.001)
NonHaz branch%		0.011 (0.004)	0.012 (0.004)
Branch number			9.476×10^{-5} (3.434×10^{-5})
Bank-level controls	Yes	Yes	Yes
Headquarter fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Average of actual value at 90 th pct. minus actual value at 10 th pct. of earthquake experience	0.002	0.002	0.002
Average of fitted value at maximum minus fitted value at minimum of earthquake experience	0.046	0.046	0.046
R-squared	0.240	0.238	0.237
Observations	16473	16473	16473
Number of banks	464	464	464

2.4.2 Lending Preferences

Borrower Income

If banks with more intense disaster experiences use their additional capital to enhance their monitoring, we expect to see a negative relationship between earthquake experiences and the average income of borrowers. But if disasters lead banks to be circumspect in lending, we expect a positive relationship. To explore which effect dominates, we rely on the HMDA dataset containing the yearly borrower income that we use as a proxy for borrower credit quality.

The results in Table 2.4 point to a significantly positive relationship between

Table 2.4: Disaster Experiences Trigger Flight-to-Quality of Banks

This table reports estimates of regressions of the income of borrowers on earthquake experiences of banks and a series of bank- and regional-specific variables. The time horizon is 2010 to 2013. We first collect the income of individual borrowers from the HMDA dataset and then calculate the yearly average of the borrower income for each bank and use it as the dependent variable. All other explanatory variables are as defined in Table 2.2. We estimate the model on a tightly spaced grid of values of the weighting parameter λ (step=0.02), and select the estimates resulting in the lowest residual sum of squares to be the final estimated coefficients. The standard errors robust to heteroscedasticity are reported in parentheses. The weighting parameters are shown in the first row. All the regressions control for year fixed effects.

	(i)	(ii)	(iii)
Weighting parameter λ	1.16	1.16	1.24
Earthquake experience coefficient β	602.318 (250.450)	657.936 (269.318)	592.535 (252.941)
NonHaz branch%		53.658 (55.099)	56.862 (56.967)
Branch number%			-1.511 (2.028)
Bank-level controls	Yes	Yes	Yes
Regional controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Average of fitted value at 90 th pct. minus fitted value at 10 th pct. of earthquake experience	65.866	71.948	68.832
Average of fitted value at maximum minus fitted value at minimum of earthquake experience	368.857	402.917	390.313
R-squared	0.193	0.189	0.178
Observations	280	280	280
Number of banks	112	112	112

earthquake experiences and borrower income, which means banks become more willing to lend to borrowers with good credit quality after experiencing more earthquakes. The economic effect of this finding is significant: an increase of the disaster experience variable from its 10th percentile to its 90th percentile corresponds to an increase in average borrower income of 69 thousand dollars.¹⁷ Such a change in

¹⁷Note in this regression we did not include the dummies for counties for the following reasons. First, the county dummies do not have a strong economic interpretation because the experience variable is an aggregate of experiences of branches that are located across several counties. The “headquarter effects” in the previous analyses is merely a far-fetched interpretation; second, controlling for them leads to poorly fitted model with negative adjusted R-squared value, high p-value, and insignificant coefficients for all variables, including the constant. In this view, we dropped these dummies of ambiguous economic meanings. Another potential identification issue is that high-income consumers may select big, renowned banks. We handle this issue by excluding all banks with more than \$2 billion total assets in the robustness test. Inferences about the relation between bank risk taking and disaster experience continue to hold in this smaller sample.

borrower composition deserves attention from policy makers: as will be elaborated in the later subsection, in the past decades counties with higher earthquake risks have witnessed an inflow of low-income households and an outflow of rich families. By inducing banks to adjust their borrower composition, disasters impose credit restrictions on low-income people who come to rebuild cities undergoing costly damages (Elliott, 2014). Such an inefficiency in credit rationing can slow down a recovery.

Borrower Race

Besides income levels, borrowers' racial composition is another measure of inequality. When banks have a subjective bias toward ethnic minorities, they may choose to reduce lending after being made more conservative by disaster experiences. And indeed, one of the purposes of the HMDA dataset is to monitor possibly discriminatory lending patterns in banks. As has been shown in the previous studies using survey data, the inequality issue exists in the lending to minorities and small business (Cole et al., 2004; Avery et al., 2005).

The results in Table 2.5, nevertheless, show that there is no link between earthquake experiences and the proportion of minority borrowers. Apparently, no news is good news. The results, however, may not be easily generalizable because we are only examining banks in California, a state well known for its ethnic diversity.

2.4.3 The Effects of Earthquake Experiences on Market Forces

In the preceding, we provide evidence of the significant impact of earthquake experiences on banks' balance sheet structure and lending preferences. For the sake of generality, we address all the dependent variables as "risk-taking measures." But in fact, except for the capital ratio that is commonly used as a measure of bank risk taking (Collier, 2014; Bouwman and Malmendier, 2015; Thakor, 2014), both real estate loans and borrower composition also reflect external market forces. Notably, unlike individuals, banks need to absorb deposits from the market and are obliged to provide liquidity to support the economy. In this view, examining changes in the market forces associated with disaster experiences is not only compelling, but is also necessary.

Market Forces and the Real Estate Lending Ratio

For the banking sector, market forces inherently contain two elements: the supply of deposits and the demand for loans. In this subsection, we show that earthquake

Table 2.5: No Significant Impact on Borrower Race

This table reports estimates of regressions of the portion of non-white borrowers on earthquake experiences of banks and a series of bank- and regional-specific variables. The time horizon is 2010 to 2013. We first collect the information of borrower race from the HMDA dataset and then calculate the portion of non-white borrowers for each bank and use it as the dependent variable. All other explanatory variables are as defined in Table 2.2. We estimate the model on a tightly spaced grid of values of the weighting parameter λ (step=0.02), and select the estimates resulting in the lowest residual sum of squares to be the final estimated coefficients. The standard errors robust to heteroscedasticity are reported in parentheses. The weighting parameters are shown in the first row. All the regressions control for year fixed effects.

	(i)	(ii)	(iii)
Weighting parameter λ	-0.04	-0.12	-0.12
Earthquake experience coefficient β	-0.270 (0.474)	-0.232 (0.555)	-0.301 (0.581)
NonHaz branch%		0.008 (0.044)	0.008 (0.045)
Branch number%			-0.001 (0.002)
Bank-level controls	Yes	Yes	Yes
Regional controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Average of fitted value at 90 th pct. minus fitted value at 10 th pct. of earthquake experience	-0.012	-0.010	-0.014
Average of fitted value at maximum minus fitted value at minimum of earthquake experience	-0.052	-0.041	-0.053
R-squared	0.510	0.479	0.464
Observations	280	280	280
Number of banks	112	112	112

experiences lead to a shortfall in branch-level deposits and explore the reason behind such drop of deposit.

We obtain deposit data from the Summary of Deposit (SOD) dataset of the FDIC. Now that the data are at the branch level, we no longer aggregate and can simply use equation (2.2) to construct the earthquake experience for each branch. The regression results on the impact of earthquake experiences on deposits are presented in column (i) of Table 2.6. The results show that branches with stronger earthquake experiences witness a significant decrease in their deposits. The economic magnitude of this differential effect is moderate: a change from the 10th to the 90th percentile of earthquake experiences is associated with a decrease in deposits of 314 thousand dollars in a bank branch.

Now coming back to a previous issue, one may ask: as banks' budget constraint is determined by savings, is the decrease in the real estate lending ratio related the shortfall of deposits? To clarify this puzzle, we plot the relationship

between bank-level deposit and real estate lending ratio in Figure 2.4 in the appendix. The top panel shows a weakly positive relationship mainly driven by a few outliers, i.e. banks with extremely high level of deposits. After excluding banks with deposits above the top 5% of the distribution, we plot the bottom panel, which indicates that there is no clear relationship between deposit level and real estate lending ratio. In this way, we disprove the market force that link this two variables and make the learning channel more convincing.

But what are the reasons for the decline in deposits? Do economic and/or demographic conditions play a role? To find the answer, we examine the impact of earthquake experiences on the median household income of California counties. Exploring the county-level income data requires the construction of county-level experiences. The procedure is similar to what we did before except we now use the date of incorporation to represent the date of establishment of the county.¹⁸ The results indicate a significantly negative relationship between earthquake experience and household income. Based on the estimates reported in column (ii) of Table 2.6, an increase in the earthquake experience from its 10th percentile to its 90th percentile implies a decrease in income of 51 dollars for each household. This shows that over the years, earthquakes have driven rich people to migrate out of the county and poor people to move in. The decrease of deposits is thus the consequence of the changes in the income structure.¹⁹

Disregarding the evidence presented here, one may be concerned that the decrease in deposits is driven by the decrease of the overall population of the county, but not by the changes in income structure. We do not find this to be the case in our tests of the effects of experiences on migration. The results in column (iii) and (iv) of Table 2.6 show that the impact is neither significant for net migration nor for net domestic migration, thus alleviating concerns of the decrease of the overall population being a confounding factor. Moreover, in line with the sociological literature on the relationship between natural hazards and residential mobility (Pais and Elliott, 2008; Schultz and Elliott, 2013), our results assert that disasters act both as an environmental “push” and “pull.” Particularly, rather than focusing on the immediate effects of disasters (Elliott, 2014; Pais and Elliott, 2008), we contribute to the literature by exploring the long-term effects of

¹⁸In the current context, incorporation means that a county has legally become or formed to be a political entity of California.

¹⁹One reasonable concern is that higher income level may not lead to more bank deposit because, instead of saving, rich families can invest in various financial assets such as bonds, stocks, and mutual funds. To bridge the link between household income and deposit level, we draw a scatter plot in Figure 2.5 in the appendix. The figure confirms that high median household income is related to high deposit level.

a series of events. So far we can conclude that disaster experiences cause wealthier people to migrate out of the county and poorer people to move in. In this way, low-income people increase their job opportunities by helping the recovery but at the cost of facing more future hazards.

Finally, we examine whether the demand for loans is affected by natural disaster experiences using the HMDA data. The HMDA data provide the ‘loan amount’ for every bank branch in the period 2010 to 2015. Again, the key explanatory variable is the county-level earthquake experience. We construct the dependent variable by averaging the loan amount across each bank’s branches in every county. Results in column (v) of Table 2.6 indicate an insignificant relationship between the demand for loans and the earthquake experience, with a negative shape parameter. The effect remains insignificant even if we force the shape parameter to a positive value (column (vi)). This finding further confirms that rebuilding activities do happen after disasters and thus stimulate the demand for loans. Further, as illustrated in the distribution map before, earthquakes are frequent in developed coastal regions. Although they are prone to natural hazards, these regions have a strong ability of attracting various types of businesses, so the demand for funds is less likely to fall.

In sum, besides banks, markets and residents also learn from their disaster experiences. Specifically, rich families living in counties with stronger earthquake hazard learn from their experiences and migrate to safer places. Such changes in the demographic structure consequently bring down the deposit level, contributing further to the decrease in real estate lending of banks in those counties.

It is worth pausing a moment to reflect on the channels linking disasters to banks’ decision making. In general, there are two routes: the first is the “learning from experience” channel that is psychological and relates to behavioral finance; the second is the “market forces” channel that is more mechanical and has a general equilibrium taste. The special features of the banking sector determine the importance of these two channels. By absorbing and lending funds, banks interact closely with local markets, and their practices largely reflect market conditions. Thus, while disasters can alter the risk attitude of banks, they can also change market conditions, especially in the long term. Therefore, while papers on individual decision making can easily reach the conclusion that disasters affect the risk attitudes of investors through the “learning channel” (Malmendier and Nagel, 2011, 2015; Bernile et al., 2017), this paper must carefully evaluate both channels. So far, though we have pointed out the role of market forces in affecting the real estate lending ratio, we cannot exclude the learning channel because doing so will require specific data such as surveys of bankers. Therefore, the conclusion so far

is that both channels can exist. However, in the next subsection, we find further evidence in favor of the “learning” channel by showing that market forces play no role.

Market Forces and the Borrower Income

In the previous subsection, we find banks with stronger earthquake experiences tend to lend to high-income borrowers. At that moment we resisted the temptation of concluding that banks become more conservative as a result of their disaster experiences, since the change in borrower composition may be related to the change in local income structure. Indeed, by exploring market forces, we find that counties with higher earthquake hazards witness a decrease in median household income. Nevertheless, in line with the “market forces” channel we may still be concerned that banks follow high-income borrowers to “migrate” (i.e. switch their activities) to less hazardous regions. As it turns out, this hypothesis is easy to reject.

Results in Table 2.6 already show that counties with stronger earthquake experiences do not witness a decrease in loan demand. In this subsection, we go a step further by examining what types of loans are likely to be given out in less hazardous counties. Doing so requires a binary choice regression model. Specifically, we use the HMDA data and denote 1 if the county is in the less hazardous region, as defined in Section 2.3, and 0 otherwise. The three loan characteristics are loan amount, borrower income, and borrower race. Results shown in Table 2.7 are based on a linear probability model, a probit model, and a logit model respectively.²⁰

We find there is a significantly negative relationship between the county indicator and the loan amount and a significantly positive relationship between the county indicator and the borrower income. Thus, although high-income borrowers are more likely to live in less risky counties, they do not necessarily borrow more. On the contrary, it is the more hazardous (costal) regions that demand more loans to support their economic development. Last but not least, the results in Table 2.7 resonate with our previous findings that low-income borrowers migrate to riskier regions. For example, in addition to showing that rich people concentrate in less hazardous regions, the significantly negative coefficients for “nonwhite applicant” also indicate that nonwhite residents tend to live in disaster-prone regions.

In short, this subsection provides further evidence against a strong link be-

²⁰Estimates in columns (ii) to (vii) are based on the randomly selected subsamples (1% full sample) because the huge number of observations in the full sample implies too few variations in the data and prevents the probit and logit models from converging. To show that the results are robust to the selection of subsamples, we run three regressions for each probit and logit model.

Table 2.6: The Effects of Earthquake Experiences on Deposits, Demographics, and Loan Demands

This table reports the effects of earthquake experiences on branch deposit, median household income, net migration, net domestic migration, and branch average loan amount respectively. The time horizon is 1994 to 2013 for the first four variables and 2010 to 2015 for the last variable. The purpose of this table is to explore the channel between the real estate loans and the supply/demand of funds of banks. The branch deposit is from the SOD dataset and represents the amount of deposit for each bank branch. The three demographic variables are at the county level. Median household income is from the U.S. Census Bureau. Net migration and net domestic migration are from the Department of Finance of California. The loan amount variable is at the bank-county level; the data come from the HMDA. The estimation method is as explained in the previous regressions. The standard errors reported in column (i) are robust to heteroscedasticity. Using robust errors for other regressions will cause Matlab to report problem message (iteration limit); this is because the values of some the explain variables are too close to each other. Since the standard errors for the insignificant β 's are so large that they will remain so even if we scale the data and apply the robust errors, we simply use the non-robust standard errors for these regressions. The weighting parameters are shown in the first row. All the regressions control for county fixed effects and year fixed effects.

	Branch Deposit	Median Income	Net Migration	Net Domestic Migration	HMDA Loan Amount	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Weighting parameter λ	1.60	4.06	1.54	3.54	-1.62	2.0
Experience coefficient β	-0.430	-0.900	14.258	2.397	-71.520	[fixed] 0.155
	(0.105)	(0.530)	(18.398)	(2.961)	(364.128)	(2.790)
Branch-level controls	Yes	-	-	-	-	-
Regional controls	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Difference in fitted value at 90 th and at 10 th pct.	-0.314	-0.051	0.615	0.129	-0.005	0.006
Difference in fitted value at max and at min	-42.714	-4.181	6.423	6.770	-0.634	0.015
Number of branches	2960					
Number of banks	549				35	35
R-squared	0.077	0.966	0.478	0.738	0.539	0.539
Observations	33576	1057	1057	1057	220	220

Table 2.7: Banks Did Not Increase Lending in Less Hazardous Regions

This table reports results of estimating binary choice regressions of “*NonHaz*” *Region* from 2010 to 2015. All variables are from the HMDA dataset. The dependent variable is an indicator equal to 1 if the county is in the less hazardous region, as defined in Section 2.3, and 0 otherwise. Loan amount is the dollar amount granted to an individual loan applicant by a bank branch; nonwhite applicant is an indicator variable equal to 1 if the loan applicant is nonwhite; and applicant income is the yearly income of the borrower. We use the linear probability model, the probit model, and the logit model. Column (i) reports results of the linear probability model based on the full sample. Estimates in the rest of the columns are based on the randomly selected subsamples (1% full sample) because the huge number of observations in the full sample implies too few variations in the data and prevents the probit and logit models from converging. For each probit and logit model, we run three regressions to show that the results are robust to the selection of subsamples. The standard errors robust to heteroscedasticity are reported in parentheses. All the regressions control for the year fixed effects.

	Linear	Probit				Logit	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
Loan amount	-0.137 (0.001)	-2.350 (0.071)	-2.436 (0.078)	-2.251 (0.084)	-4.943 (0.131)	-4.809 (0.145)	-4.663 (0.134)
Applicant income	0.020 (0.001)	0.078 (0.068)	0.118 (0.063)	0.188 (0.061)	0.266 (0.112)	0.144 (0.161)	0.001 (0.101)
Nonwhite applicant	-0.022 (0.000)	-0.117 (0.022)	-0.085 (0.021)	-0.075 (0.021)	-0.124 (0.042)	-0.209 (0.043)	-0.155 (0.042)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.023	0.078	0.081	0.071	0.081	0.079	0.076
Observations	4,249,491	42,495	42,495	42,495	42,495	42,495	42,495

tween market forces and the borrower income level of banks. At this moment, we can confirm that the increase in borrower income for banks with stronger earthquake experiences is because these banks have become more conservative after learning from their experiences.

2.4.4 Robustness

In this subsection, we carry out a series of tests to evaluate the robustness of our baseline analyses and basic inferences.

Different Thresholds for Selecting Earthquakes

The first robustness test is related to concerns about the ad hoc threshold used for selecting earthquakes. As discussed in Section 2.3, an earthquake is included in our sample for the baseline analyses if it has a magnitude no less than 4, which means that we implicitly posit that banks ignore earthquakes weaker than this magnitude. To ensure the robustness of our major inferences, in Table 2.8, we estimate the models using two different thresholds (magnitude=2.5 and 5), presuming that

banks ignore earthquakes weaker than 2.5 (and 5).²¹ To save on estimation time, we fix the values of the shape parameters at their previously estimated values in column (iii)’s of Tables 2.2, 2.3, and 2.4.

The results in Table 2.8 are largely congruent with the results in our baseline analyses. First, the differential effects remain unchanged. For example, the results indicate that a spread between the 10th and the 90th percentile of disaster experiences generates a change in the real estate lending ratio of about 2 percent. Second, the results imply that a one standard deviation increase in earthquake experiences is associated with a decrease in the real estate lending ratio of about 1 percent.²² However, even though the economic magnitudes do not change, the values of the β coefficients are different from the baseline results. Specifically, Table 2.8 shows that as the threshold rises, the coefficients also become larger significantly. This is because as the threshold rises, the branch-level experience becomes zero for weaker earthquakes and the resultant distribution of the experiences becomes more concentrated, leading to increases in β values.

High-Income Borrowers Prefer Large Banks

In our baseline analyses, we show that banks having stronger disaster experiences tend to extend their funds to high-income borrowers. This conclusion, however, can be discredited by a potential reverse-causality problem: in order to obtain more advanced financial services, high-income borrowers are likely to choose large banks. These banks have stronger earthquake experiences due to their large number of branches and long operating histories. This mechanism could lead to spurious effects of banks’ disaster experiences on the borrower income level.

We address such concerns in two ways. First, our previous tests control for bank size variables (e.g. total assets and number of branches). Since these controls are highly positively correlated with the experience variables, by including them, we largely mitigate the omitted-variable problem. Second, to further alleviate any reverse-causality concerns, we exclude all banks with assets above \$2 billion from our sample. The results presented by Table 2.9 show that our main inferences are unchanged.

²¹By choosing the threshold=2.5, we effectively include all earthquakes in our data, for 2.5 is the lowest magnitude in the USGS dataset. According to the description on the USGS website, earthquakes with magnitudes between 1.0 and 3.0 are not felt except by a very few under especially favorable conditions.

²²The effects of “one standard deviation in experience” are evaluated during running the programs and are not reported.

Table 2.8: Robustness: Changing the Thresholds for Selecting Earthquakes

This table reports estimates of regressions of dependent variables (given in column titles) using the fully specified models in Tables 2.2, 2.3, and 2.4. To reduce the estimation time, we fix the shape parameter λ at their previous values estimated with the full specifications. In Panel A, we include earthquakes with magnitudes greater or equal to 2.5. In Panel B, we confine the earthquake sample to events with magnitudes greater or equal to 5. All corresponding controls and fixed effects from Tables 2.2, 2.3, and 2.4 are included by not shown for brevity. The standard errors robust to heteroscedasticity are reported in parentheses.

	Capital ratio	Real estate ratio	Borrower income
	(i)	(ii)	(iii)
Panel A: Magnitude ≥ 2.5			
Weighting parameter λ	0.28 [fixed]	0.18 [fixed]	1.24 [fixed]
Earthquake experience coefficient β	3.325×10^{-4} (0.000)	-0.010 (0.001)	32.072 (12.155)
Average of actual value at 90 th pct. minus actual value at 10 th pct. of earthquake experience	0.002	-0.026	75.733
Average of fitted value at maximum minus fitted value at minimum of earthquake experience	0.046	-0.379	395.977
Panel B: Magnitude ≥ 5			
Weighting parameter λ	0.28 [fixed]	0.18 [fixed]	1.24 [fixed]
Earthquake experience coefficient β	0.063 (0.009)	-1.071 (0.124)	807.470 (1512.808)
Average of actual value at 90 th pct. minus actual value at 10 th pct. of earthquake experience	0.002	-0.022	13.671
Average of fitted value at maximum minus fitted value at minimum of earthquake experience	0.046	-0.293	73.195
Bank-level controls	Yes	Yes	Yes
Regional controls	No	Yes	Yes
Headquarter fixed effects	Yes	Yes	No
Year fixed effects	Yes	Yes	Yes
Observations	10625	10595	10545
Number of banks	415	415	415

Rescaling the Magnitude

Some readers may doubt that the Richter magnitude scale we use is not a linear measure, which makes our results to be less convincing. We point out that this

Table 2.9: Robustness: Borrower Credit Quality (Excluding Large Banks)

This table reports estimates of regressions of the income of borrowers on earthquake experiences of banks and a series of bank- and regional-specific variables. The time horizon is 2010 to 2013. We first collect the income of individual borrowers from the HMDA dataset and then calculate the yearly average of the borrower income for each bank and use it as the dependent variable. To address the potential reverse-causality concern, we exclude all banks with assets above \$2 billion from our sample. We fix the shape parameter λ at their previous values estimated in Table 2.4. The standard errors robust to heteroscedasticity are reported in parentheses. The weighting parameters are shown in the first row. All the regressions control for year fixed effects.

	(i)	(ii)	(iii)
Weighting parameter λ	1.16 [fixed]	1.16 [fixed]	1.24 [fixed]
Earthquake experience coefficient β	631.162 (277.031)	630.942 (293.373)	522.954 (280.341)
NonHaz branch%		-1.112 (75.189)	1.731 (77.838)
Branch number%			-6.209 (5.824)
Bank-level controls	Yes	Yes	Yes
Regional controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Average of fitted value at 90 th pct. minus fitted value at 10 th pct. of earthquake experience	76.914	76.887	66.768
Average of fitted value at maximum minus fitted value at minimum of earthquake experience	386.371	386.237	344.355
<i>R</i> -squared	0.196	0.184	0.171
Observations	246	246	246
Number of banks	92	92	92

concern is not necessary. The nonlinear property of the Richter scale refers to the amplitude of the earthquake. For example, an earthquake with a magnitude of 5 has a shaking amplitude ten times greater than an earthquake of magnitude 4. But what matters in our analysis is the intensity of the earthquake, and magnitude and intensity do have a positive linear relationship. As magnitude is one number for each earthquake but there are many intensities for an earthquake depending on where the people who feel the earthquake are, we decide to use the magnitude in this analysis.

Nevertheless, we still do a robustness test by rescaling the magnitudes by taking the natural and base-10 exponentials for magnitudes respectively. Panel A and B in Table 2.10 report the results. By fixing the shaping parameter values, the differential effects remain intact in Panel A while they almost halve in Panel B.

Table 2.10: Robustness: Rescaling the Earthquake Magnitude

The earthquake magnitudes in our data are based on the Richter Scale that is a base-10 logarithmic scale. However, for simplicity, the previous results treat the scale to be linear. In this table, we rescale the magnitudes by taking the natural exponential as well as the base-10 exponential respectively. The table reports regression estimates of earthquake experiences on capital ratio, real estate lending ratio, and borrowing income. We fix the shape parameter λ at their previous values estimated using the full specifications.

	Capital ratio	Real estate ratio	Borrower income
	(i)	(ii)	(iii)
Panel A: Natural Logarithm			
Weighting parameter λ	0.28 [fixed]	0.18 [fixed]	1.24 [fixed]
Earthquake experience coefficient β	3.325×10^{-4} (0.000)	-0.010 (0.001)	30.590 (12.734)
Average of actual value at 90 th pct. minus actual value at 10 th pct. of earthquake experience	0.002	-0.031	75.910
Average of fitted value at maximum minus fitted value at minimum of earthquake experience	0.034	-0.454	412.877
Panel B: Base-10 Logarithm			
Weighting parameter λ	0.28 [fixed]	0.18 [fixed]	1.24 [fixed]
Earthquake experience coefficient β	1.801×10^{-7} (0.000)	-8.049×10^{-4} (0.000)	0.047 (0.025)
Average of actual value at 90 th pct. minus actual value at 10 th pct. of earthquake experience	0.001	-0.019	57.576
Average of fitted value at maximum minus fitted value at minimum of earthquake experience	0.036	-0.192	323.607
Bank-level controls	Yes	Yes	Yes
Regional controls	Yes	Yes	Yes
Headquarter fixed effects	Yes	Yes	No
Year fixed effects	Yes	Yes	Yes
Observations	16473	10545	280
Number of banks	464	415	112

2.4.5 Can Disasters Make Banks More Risk Loving?

Thus far, we have shown that stronger disaster experiences lead banks to reduce real estate lending, boost their capital adequacy, and lend more to high-income borrowers. These relationships, however, are implicitly presumed to be monotonic. We might suspect, however, that banks that continuously survive moderate disasters may believe that they are resilient to adverse events and thus become overconfident. This concern echoes with the recent findings by Bernile et al. (2017) who

show that CEOs with moderate early-life natural disaster experiences are more willing to make riskier financial decisions than CEOs whose experiences are at the low and high extremes of the distribution of disaster experiences. To explore such a dimension of heterogeneity in the banking sector, we classify banks into ten groups by the deciles of their earthquake experiences and analyze each subsample, fixing the shape parameter λ at their previously estimated values. Figure 2.3 shows the estimated effects of earthquakes (β) and their t -statistics for each decile group.

The figure demonstrates a few things. Specifically, we find banks who are the least exposed to earthquakes tend to extend a significantly larger amount of real estate loans and maintain a lower level of capital. For instance, for banks in the bottom decile group, increasing the experience from its 10th percentile to its 90th percentile leads to a decrease in capital ratio of about 1.1 percent. Given that the standard deviation of the capital ratio is 2.8 percent for these banks, the economic magnitude is sizable. This means that banks that experienced very few extreme disasters are more risk-loving than banks whose disaster experiences are stronger. However, as the earthquake experiences accumulate, banks reduce their real estate lending, increase their capital adequacy, and finally invert the relationship. In contrast to Bernile et al. (2017), our plots show an almost monotonic relationship between disaster experiences and measures of bank risk taking. These two pieces of evidence are not easily compared because the samples and the measures of disaster experiences are so different. But at least both indicate that the beliefs of decision makers about future risks depend heavily on the disaster intensity.

Figure 2.3: Banks with the Least Earthquake Experiences Become Risk-Loving. This figure plots the estimated effects of earthquakes (β) and their t -statistics by the deciles of earthquake experiences for real estate loan, capital ratio, and borrower income level. In the plots of the β coefficients, we add the 95% confidence intervals. In the plots of the t -statistics, we draw two reference lines to denote the critical t -values at the 95% confidence level. Plots for the borrower income omit the first estimate due to lack of variation in the data; also, the reference lines for the t -values are based on the 90% confidence level.

2.5 Conclusion

This paper studies the relationship between disaster experiences and the business practices of banks. California offers an ideal setting for identification. It has a comprehensive record of earthquakes dating back to the 18th century and its socio-economic variables are easy to access. Exploiting the completeness of the data, we manage to identify the long-term impacts of disaster experiences on balance sheet structure and lending preference and to explore the evolution of market forces underlying such changes.

We find banks with bigger earthquake exposures throughout their lives tend to issue less real estate loans, increase the equity level, and are more likely to lend to high-income borrowers. Our empirical results show that an increase in the earthquake experience from its 10th percentile to its 90th percentile leads to a decrease in real estate lending ratio of about 3.1 percent and an increase in average borrower income of around 69 thousand dollars. Fortunately we do not find evidence that strong earthquake experiences lead banks to discriminate more against ethnic minorities.

Banks interact closely with local markets, so both subjective risk taking and the external market forces determine their balance sheet structure. With the assistance of our detailed data, we initially confirm that both channels exist. First, counties that frequently experience earthquakes in their history witness an outflow (inflow) of rich (poor) households and consequently a decrease in income level. This drop in the income level contributes to the decrease of deposits. These results thus point to a general equilibrium channel. Second, even though rich families migrate out of risk-prone counties, banks did not follow them by increasing their lending activities in those less risky counties where rich people are concentrated. As a matter of fact, most lending activities concentrate in riskier regions, perhaps due to the strong demand for funds of the coastal area. The increased borrower income therefore is not led by changes in market forces but is mostly related to banks learning from disaster experiences.

Our main results remain stable under a battery of robustness tests. In particular, the test designed to explore the heterogeneous effects of disaster experiences reveals that banks with extremely small disaster exposure become risk loving. But as experiences accumulate, the dependent variables alter monotonically and the risk attitude inverts.

Although our results are robust and statistically significant, the economic magnitude is on average modest. This is not necessarily a defect as we have pointed out and tested various forces, many of which are in opposite direction, that drive

our measures of balance sheet structure and lending preferences. Meanwhile, when we calculate the differential effects using the maximum and minimum values of the experience, the economic magnitude appears large. Since disasters are highly unevenly distributed over the world, the effects of disaster experiences on financial systems of different countries will be non-negligible.

Finally, the positive yet near-zero values of the shape parameter imply an almost flat memorizing curve of disasters. Therefore, even shocks happened far back in the past do not fade away easily and still influence current financial decisions. Moreover, compared with the values of the shape parameter estimated in Malmendier and Nagel (2011, 2015), those in our paper are even lower, indicating that institutions retain longer memories than individuals do. In view of the long-lasting effect of shocks and the intermediate role of the banking sector, building a general equilibrium learning model to account for the long-term influence of disasters is an important future endeavor.

Appendix

Table 2.11: Terminology

This table lists definitions of the key concepts used in this paper and dependent and explanatory variables compiled from the original data.

<i>Concepts</i>	
California	California is a state of U.S. located on the western (Pacific Ocean) coast. Its dominant natural disasters are earthquake and wildfire.
Natural disaster	A natural disaster is a major adverse event resulting from natural processes of the Earth; examples include floods, volcanic eruptions, earthquakes, tsunamis, and other geologic processes.
Earthquake	An earthquake is the shaking of the surface of the Earth, resulting from the sudden release of energy in the Earth's lithosphere that creates seismic waves.
<i>Dependent variables</i>	
Real estate ratio	Loans secured by real estate/total assets; source: Call Reports; frequency: quarterly.
Capital ratio	Total equity capital/(total assets+allowance for loan and lease losses+allocated transfer risk reserves); also know as equity ratio, equity capital ratio, or capitalization; source: Call Reports; frequency: quarterly.
Borrower income	Average borrower income (yearly) across all branches of a bank; source: HMDA dataset; frequency: yearly.
Borrower race	Number of nonwhite borrowers/number of all borrowers of a bank; source: HMDA dataset; frequency: yearly.
<i>Explanatory Variables</i>	
Bank/branch age	The number of dates between the date of establishment and the date of the observation of the dependent variable. For instance, for the value of real estate ratio in the 4th quarter of 2010, the bank/branch age equals 2010-12-31 minus the date of establishment.
Branch number	Number of branches of a bank; source: SOD dataset; frequency: yearly.
Imputed interest rate	Interest income/ outstanding loans of the last quarter; source: Call Reports; frequency: quarterly.
NonHaz region	counties that has significantly less earthquakes, including replace Amador, Butte, Calaveras, Colusa, El Dorado, Sacramento, San Joaquin, Stanislaus, Sutter, Tuolumne, Yolo, and Yuba.
NonHaz branch%	The proportion of a bank's branches in the <i>NonHaz region</i> .
ROA	Return on assets. Net interest income/ total assets of the last quarter; source: Call Reports; frequency: quarterly.

Figure 2.4: Closing the Circle: Relationship between Bank Deposits and Real Estate Lending Ratio. This scatter plot shows the relationship between bank-level deposits and real estate lending ratio. The full sample is the same as used in Table 2.2 and the subsample excludes outliers defined as banks whose deposits are at the top 5% distribution.

Figure 2.5: Closing the Circle: Positive Relationship between Median Household Income and County-Level Deposits. This scatter plot shows the relationship between county-level median household income and county-level bank deposits. The income data are from the U.S. Census Bureau and the deposit data are from the SOD dataset of FDIC. We sum branch-level deposit by county and year to get the county-level deposit. The fitted regression line confirms the positive relationship between the two variables.

Hazardous Lending: The Impact of Natural Disasters on Banks' Asset Portfolio

3.1 Introduction

This paper studies how banks adjust their asset structure in response to changes in loan demand after natural disasters. We first show that natural disasters affect the composition of loans and securities in the empirical analysis. We then establish a dynamic credit rationing model to illustrate the underlying mechanisms, and calibrate and simulate our model to reproduce our empirical findings.

In a broader point of view, our research concerns the credit rationing issue, a central topic of banking research.² Against the background of climate change, natural disasters are likely to become more frequent (Pachauri et al., 2014) and have received more attention from researchers. As a result, an emerging strand of literature discusses how banks geographically reallocate assets to meet disaster-driven increases in demand (Chavaz, 2014; Cortés and Strahan, 2017), how natural disasters affect banks' solvency (Klomp, 2014), and how bank-borrower relationships can affect borrowers' access to credit after natural disasters (Berg and Schrader, 2012; Koetter et al., 2016).

To the best of our knowledge, however, there are no papers that study how banks would adjust the composition of their asset portfolio in response to disasters. A diversification strategy to manage natural hazards risks is important for banks as it is easy to implement and provides banks with a powerful natural hedge against losses. By strategically (re)allocating assets, banks can better serve the increased loan demand after disasters and thereby aid the recovery of local economies (Dlugosz et al., 2017).

To understand how banks diversify assets in response to natural hazards, in this study, we carry out both empirical and theoretical analyses to examine how natural disaster affect banks' asset allocation. Both analyses use the Call Reports that contain information of all U.S. commercial banks' balance sheet data over a

This chapter is co-authored with Jaap Bos (Maastricht University) and Mark Sanders (Utrecht University).

²There is a long list of papers on banks' credit rationing. Theoretical papers include Stiglitz and Weiss (1981), Brunnermeier et al. (2012), and Gorton and He (2008). Empirical studies on the lending behavior include Hannan and Berger (1991), Angbazo (1997), Asea and Blomberg (1998), Carling and Lundberg (2005), and Zecchini and Ventura (2009).

period of 45 quarters from 2002 to 2013. In addition, we make use of two natural disaster datasets. The major one is the EM-DAT dataset that gives us detailed information about the time, location, type, magnitude, and damage of natural disasters. The one we use as a reference is the Federal Emergency Management Agency’s records of major disaster declarations of the U.S..

In the empirical section, to infer the causal effect of natural disasters on bank behavior, we apply the difference-in-difference (DID) analysis and estimate disasters’ impact on asset quantities of commercial banks, choosing a ± 1 year window. Using the 86 most costly natural disasters in the U.S. between 2001 and 2013, we find that the amounts of total loans and real estate loans significantly increase after natural disasters, while the holdings of government bonds decrease. This result is robust to different lengths of the event window and is consistent with previous findings that confirm residents increase their demand for mortgage loans and banks react to it by selling government securities (Cortés, 2017).

In the theoretical section, we develop a dynamic credit rationing model with multiple assets. In our model, natural disasters destroy firms’ capital, leading to a surge in the demand for loans and an increase in the borrowing rate. The impact of disasters on banks are twofold. On the one hand, banks first suffer delayed or defaulted loan payment as disasters destroy borrowers’ capital. On the other hand, banks have the opportunity to exploit the increased demand and interest rates.

We calibrate the model so as to match the key financial ratios implied by the model with the real data. After that, we simulate a negative disaster shock on entrepreneurs’ capital in order to replicate our empirical findings. Our simulation results indicate that banks increase the issuance of loans that charge higher interest rates and sell government securities to finance their lending business. By doing this, banks benefit in two ways. First, banks can satisfy the demand for loans from the public and therefore aid the recovery. Second, banks increase their revenue and compensate for the losses due to disaster-related defaults. Finally, we simulate scenarios of climate change to see how banks reallocate assets and the implications for banks’ capital ratio and income. We show that an increase in the perceived disaster probability due to climate change is associated with decreased lending, a lower level of capital ratio, less revenue, and more holdings of government bonds.

Our paper has three contributions. First, we find that banks adjust their asset structures after natural disasters. Specifically, banks issue more loans secured by real estate and sell government bonds to finance such increased lending. Second, we model such a change in the asset structure to be driven by the disaster-related demand shock. In this process, banks issue more loans and can charge a bit higher

prices for these loans, but in the mean time, have to sell government securities. Our model has the feature of producing the interactions among multiple assets in a dynamic setting. To our knowledge, this feature has not yet been addressed in other literature.

Our paper is related to two strands of literature. At the macroeconomic level, our paper is related a handful of recent papers emphasizing the role of financial institutions in natural disaster alleviation and recovery. Toya and Skidmore (2007) report that countries with more complete financial systems suffer fewer economic losses after natural disasters. Noy (2009) corroborates that a higher level of domestic credit enhances a country's resilience to disaster shocks, but meanwhile points out that countries having less open capital accounts are more robust to natural disasters. Loayza et al. (2009) examine the impact of natural disasters on growth by disaster and industry type and assert that developing countries have more industrial sectors affected than developed countries.

Concerning the micro-level behavior that explains the above phenomena, our paper is most related to the recent literature of credit dynamics during natural disaster times (Berg and Schrader, 2012; Chavaz, 2014; Koetter et al., 2016; Cortés and Strahan, 2017; Dlugosz et al., 2017). For example, Berg and Schrader (2012) show that the demand for credit increases after volcanic eruptions in Ecuador. Further, the authors find that bank-firm relationships positively predict firms' access to credit. Focusing on the supply side, Chavaz (2014) shows that local banks of disaster-struck regions possess more private information of borrowers than geographically diversified banks. During the 2005 U.S. hurricane season, local banks, through loan sales, could circumvent capital constraints and satisfy firms' increased mortgage demands. Cortés and Strahan (2017) find that banks geographically reallocate funds when local credit demand increases after natural disasters. Moreover, they find banks increase sales of more-liquid loans to lessen the impact of the demand shock on credit supply. In this paper, rather than focusing on the geographic distributions of assets, we propose that reallocation of resources within a bank can also smooth its income and is beneficial to banks and the local community.

The theoretical model in our paper is closely related to Collier (2014) who sets up a dynamic lending model and evaluates the impact of disaster-related credit risk on the loan supply to small enterprises. The model predicts that lenders suffer losses in their income and therefore contract credit after big natural disasters, which is supported by data of a small business lender in Peru after the severe El Niño-related flooding of 1998. Instead of focusing on the payment shock, our paper

incorporates the demand side of loans, i.e. the production sector, and examines the demand shock that follows natural disasters. In fact, the payment shock is caused by the disaster shock to firms' capital. By linking the payment shock and demand shock together, our model becomes more general and helps us understand the behavior of both the demand and supply sides.

In short, the successful management of assets after a natural disaster not only compensates the bank from losses due to disaster-induced defaults and delayed payments, but also guarantees banks' ability in supporting communities. Our effort in understanding banks' asset allocation thus becomes meaningful to both banks and communities.

The outline of the paper is as follows. Section 3.2 introduces the data. Section 3.3 uncovers how natural disasters affect banks asset allocations. Section 3.4 presents our theoretical framework, calibrates the model, and compares model and data moments. Section 3.5 simulates the impact disaster shocks and climate change. Section 3.7 concludes.

3.2 *Data and Descriptive Statistics*

To establish the stylized facts we are primarily interested in in this paper, we collect data on individual banks' balance sheet composition, the market prices for these asset categories and data to identify which banks were in a region that was affected by a natural disaster. The banks' balance sheet items are from banks' Call Reports, and the disaster records are from EM-DAT (Guha-Sapir et al., 2015) and FEMA. We also collect the state-average interest rates from Uniform Bank Performance Reports (UBPRs). In the next two subsections, we first discuss our data collection procedure and then present descriptive statistics.

3.2.1 *Data Collection*

Balance Sheet Variables

The data on loans, securities, deposits, and equity are from the Call Reports of all federally insured commercial banks in the United States. Our sample covers 45 quarters from 2002:Q4 to 2013:Q4 and includes 356,452 bank-level observations in total. From this source we extracted and compiled loans secured by real estate, commercial and industrial loans, consumer loans, federal government securities,

total loans, total assets, and total equity.³

Interest Rates

The rates of returns on assets are not in the Call Reports but are recorded in the Uniform Bank Performance Reports in the chapter “Noninterest Income, Expenses and Yields.” The UBPRs collect variables at the state-level, so the rates are the state averages. For example, UBPRs define the yield on real estate loans as the “interest and fees on domestic office loans secured primarily by real estate, divided by average domestic real estate loans.” In addition to the interest rates, we obtain from the UBPRs the net loan loss rates which are used to calibrate the non-repayment rates in the model. As individual bank interest rates do not deviate from the state average, we model the bank as a price taker.

We plot the processes of interest rates in Figure 3.8 in the Appendix. The figure shows remarkably high correlations among all types of assets: all the interest rates proceed almost in parallel. It is thus reasonable for us to model the interest rate to be the sum of a common prime lending rate determined by the production sector and a risk premium of a specific asset.

Disasters

We acquire the disaster data from two sources. Our first data source is the EM-DAT, a comprehensive dataset of disaster characteristics. The dataset includes the worldwide natural disasters of all types and records the dates, human death toll, material damages, and geographic locations of the disasters. We extract disasters happened in the U.S. from 2001 to 2013 and select disasters whose costs are in the top 5%, leading to 86 disasters for the analysis. We match the location of each disaster with counties and classify counties into treatment and control groups in our following difference-in-difference (DID) analysis.

Second, we also look at the disaster declaration records from the Federal Emergency Management Agency (FEMA) between 2000 and 2015. Each declaration item contains 4 variables: the date, the state, the type of the disaster, and the declaration type. The types, unluckily, are not recorded in a uniform manner. For instance, fires are often recorded together with the name of their locations;

³The federal government securities include the U.S. Treasury securities and the U.S. Government agency obligations. When we refer to “government security” or “government bond”, we mean the sum of these two items. We do not, however, include the “local government securities” which are securities issued by states and political subdivisions in the U.S. because these two types of securities have different interest rates according to the Chapter “Noninterest Income, Expenses and Yields” of the UBPR.

hurricanes and tropical storms are termed interchangeably; and floods are sometimes recorded alone but occasionally recorded with other disasters such as winter storms or severe storms. As the FEMA data is not as detailed and well-sorted as the EM-DAT data, we only use it as a reference and calculate the disaster probability for each state based on the FEMA records.

3.2.2 Descriptive Figures and Statistics

Bank Variables

To give an overall impression of our sample, we show summary statistics for the major bank variables in Table 3.1. The table includes the mean, standard deviation, 10th and 90th quantile values at the bank-quarter level. To account for the effect of bank size, we divide banks into small bank (Panel A) and large bank (Panel B) groups according to their total assets. The large standard deviations in both panels indicate that the samples include heterogeneous banks across the country. Furthermore, the statistics reveal that loans secured by real estate account for nearly 50 percent of the total assets. Since this type of loan is secured by real estate, it is safer compared to other types of loans, which have either other kinds of collaterals or no collaterals at all.⁴ Interestingly, despite the different amount of loans for the two bank groups, the relative ratios are approximately the same regardless how big the bank is. For example, the level of the real estate loan is about four times as bigger as commercial and industrial loans, and are about seven times as bigger as consumer loans. This indicates that banks on average have a similar asset composition.

Disaster Frequency

In this study, we use two disaster datasets, the EM-DAT and FEMA. We use disasters recored in the EM-DAT for our empirical analysis because it provides us with precise geographic coordinates and detailed damage information, including the human and material costs. The FEMA dataset, however, only contains information about the date, state, type of disaster, and type of declaration of natural hazards. The records are far less uniform than the records in the EM-DAT. But since it is authoritative and indicates which disasters should be count as major disasters from the view of the authority, we use the FEMA as a reference.

By examining disaster records in both the EM-DAT and FEMA datasets, we find that, first, natural disasters are very prevalent in the U.S.. For example, in the

⁴For more detailed explanation on the role of collateral, see Gan (2007) and Chaney et al. (2012).

Table 3.1: Key Statistics

This table displays statistics for variables using Call Reports data that cover all commercial banks in the United States. All the variables are in millions of dollars. The mean, standard deviation, 10th percentile, and 90th percentile are based on individual bank-quarter observations. To account for the effect of bank size, we group banks into small bank (Panel A) and large bank (Panel B) groups according to their total assets. The medium of total assets is around \$0.1 billion. Banks with total assets less than \$0.1 billion are classified as small banks whereas banks having assets between \$0.1 and \$9 billion are large banks. We choose \$9 billion as the upper limit because it is already beyond the 99.5th percentile and the remaining bigger numbers can be treated as outliers.

	Average	Standard Deviation	10 th Percentile	90 th Percentile	Observations
Panel A: Small Banks (<\$100 million in assets)					
Total Assets	53.900	24.952	20.727	89.388	130908
Total Loan	32.814	19.114	9.449	60.563	130908
Real Estate Loan	21.047	15.383	4.043	43.424	130908
C&I Loan	5.025	4.982	0.745	11.027	130908
Individual Loan	2.821	2.985	0.425	6.135	130908
Government Securities	5.236	6.476	0	13.516	130908
Total Equity	6.389	4.000	2.352	10.691	130908
Deposit	37.569	18.555	13.422	63.323	130908
Panel B: Large Banks (\$100-9000 million)					
Total Assets	642.871	2666.346	116.679	991.604	177861
Total Loan	422.952	1860.527	70.209	669.344	177861
Real Estate Loan	287.145	1044.587	42.972	495.646	177861
C&I Loan	63.493	345.393	5.319	102.488	177861
Individual Loan	51.401	1050.935	1.110	32.859	177861
Government Securities	31.362	187.644	0	59.419	177861
Total Equity	68.837	361.937	11.114	99.477	177861
Deposit	395.771	1415.997	80.275	651.487	177861

western territory, wildfires are the biggest natural threat, while in the gulf coast region, floods and tropical storms are the most frequent hazards. Second, the costs of natural disasters are highly skewed. As shown in the EM-DAT dataset, among the 1707 recored natural disasters in the U.S. during 2001 and 2013, disasters that cause greater than \$1 billion losses account for 3.51 percent, while zero-cost disasters are about 85.47 percent. Among these zero-cost events, around 30.71% are wildfires and 20.08% are tornados. Among the top 5 percent most costly disasters, around 90% are floods and hurricanes. Given these disasters are prevalent and that they can affect a large area, we therefore choose a radius of 200km to identify the affected counties in our empirical analysis; this relatively large radius yields on average 50 affected counties for each disaster.

To give a further impression about the type and frequency of disasters, we plot the following figures based the FEMA disaster records. Figure 3.1 counts the number of declared “major disasters” based on FEMA records from 2000 to 2015. The figure indicates that the most prevalent countrywide natural disaster is flood, whereas wildfire is the most common natural disaster for States in the western part of the U.S. such as Texas, California, and Wyoming.

In addition, based on the major disaster declarations, we calculate the quarterly probability of natural disasters for each state. For example, Louisiana has declared 20 major disasters between 2000 and 2015, and therefore the average quarterly frequency of natural disasters is $20/(16 \times 4) = 31.25\%$. Figure 3.2 plots the histogram of disaster counts. Based on this graph, we calculate the average quarterly disaster probability for each state to be about 22.85%. This value will be used as the bank’s subjective perception of the disaster probability when we calibrate the model.⁵

3.3 Empirical Analysis

In this section, we test how banks react to disaster-driven demand shocks. Consistent with Cortés (2017), we find that natural disasters lead banks to increase the amount of loans secured by real estate and decrease holdings of government bonds. We also look at other types of assets such as commercial&industrial loan, consumer loan, and total loans. We show decreases (increases) in the amount of commercial (consumer) loan. Overall, the amount of total loans increase after

⁵Knowing the exact value of bank’s subjective disaster probability is impossible. We follow the common practice in the disaster and business cycle literature by calculating the probability based on realized disasters (Barro, 2006; Gabaix, 2008; Barro, 2009; Gourio, 2012; Wachter, 2013; Barro, 2015).

Figure 3.1: Counts of Natural Disaster Declarations (2000 to 2015). This figure displays the frequencies of each one type of the five disasters for every state. The data includes disaster declarations available on the website of the Federal Emergency Management Agency (FEMA).

Figure 3.2: Distribution of Quarterly Frequency of Major Disasters. This figure exhibits the histogram of quarterly average frequencies of “major disasters” across different states and territories of the U.S.. The data comes from the FEMA. Based on this histogram, we calculate the average disaster frequency to be 22.85%. This value will be used in our model as the bank’s perceived disaster probability to calibrate the model.

Figure 3.3: Distribution of Costs of Natural Disasters. This figure shows the distribution of all types of natural disasters in the U.S. based on the costs (millions of dollar) records from the EM-DAT dataset. Counties are determined by the geographical coordinates of the events in the data. Furthermore, counties within 200km radius of the disaster location are also included. The costs are averaged over the disasters if one region suffer more disasters during this time period. The gray color represent counties that experience no disasters during the recorded period. There are 3109 counties; the time horizon is 2001 to 2013.

natural disasters. In baseline analysis, we choose a ± 1 year event window. We use other event windows for our robustness tests shown in the Internet Appendix.

3.3.1 Identification and Methodology

To identify the causal effect of natural disasters on banks' balance sheets, we rely on a difference-in-difference (DID) analysis. That is, we identify the impact by looking at the difference between affected and non-affected banks in the *change* of balance sheet composition over time. The implicit assumption is that all banks experience similar shocks over time causing them to change their balance sheet composition and the impact of a disaster is equal to the (average) difference in this change. To give the reader an impression of the cost of disasters in the U.S. We plot the geographical distribution of disaster costs based on our EM-DAT data in Figure 3.3.

In the following analysis, we select the most costly 5% recorded disasters in our EM-DAT data set, which finally leads to 86 events. We choose large-scale disasters to make sure that these disasters are unpredictable even if firms and banks already have their subjective beliefs about the risk of disaster and are to some extent prepared for common disasters. These big disasters can significantly affect productive capital of nearly all local firms, subsequently causing loan default,

increasing credit demand, and driving up borrowing costs.

We form our sample in the following way. First, for each event, we identify the affected and unaffected counties. We define a county to be affected by a natural disaster if this county is located within 200km radius of the recorded disaster center and unaffected if this county is located between 300km and 400km radius of the disaster center. This grouping method leads to the number of affected and unaffected counties to be around 50 each, which is a reasonable number given that most of our selected disasters are hurricanes, floods, and severe weathers that affect a large region. Second, we merge each event to the bank dataset using county as the identifier and form a bank-event dataset. Finally, we append all the bank-event datasets to get our analyzing sample.

We examine the average effect of all the selected events using the following empirical model:

$$y_{bct} = \beta_0 + \beta_1 Affected_c \times PostDate_t + \gamma X_{bct} + CountyFE + TimeFE + \epsilon_{bct}, \quad (3.1)$$

where y_{bct} represents the quantity or price of an asset of bank b located in county c at quarter-year t . *Affected* equal 1 if a counties is affected, and 0 otherwise. *PostDate* equals 1 if the observation date t is after the end date of the event recored in the EM-DAT. The county fixed effects and time fixed effects capture unobservable regional traits and macroeconomic conditions that may confound with disaster-driven demand shocks. In line with Koetter et al. (2016), we control in X_{bct} for bank-specific variables including bank size (total assets), capital adequacy (total equity/total assets), liquidity (non interest bearing cash/total assets).

3.3.2 Results of DID

We present the baseline results of our DID analysis in Table 3.2. As has explained in the last section, we divide banks into small and large groups to reduce the possible distortion effect of bank size. In the current baseline results, we use a ± 1 year event window centered on the date of the disaster.

Our results show banks increase real estate loans and decrease holdings of government securities after disasters, which is consistent with Cortés (2017). The coefficients are both statistically and economically significant. For example, small banks in the affected counties on average increase real estate lending by \$0.961 million than those in unaffected counties. Given the average amount of real estate loans of \$21.047 million, as shown in Table 3.1, this is a 4.6% increase. Meanwhile, large banks increase their real estate loans by \$2.71 million, which is a 1% increase compared to the average amount. As for government bonds, small and large banks

decrease their holdings by \$0.227 and \$1.025 respectively, corresponding to a 4.3% and 3.3% decrease from the average level. In a recent study by Schwer et al. (2018), using Hurricane Katrina as a natural experiment, the authors also find significant increase in government bonds of affected banks.

In addition, we find banks increase their credit supply to households and individuals (i.e. consumer loans) and decrease lending to the commercial and industrial sector. In the ± 1 year event window setting, these results are not statistically significant. However, when we increase the event window to ± 3 years, as show in Table 3.3, we find significant coefficients for both types of loans, especially for small banks and the results for real estate loans, government securities, and total loans remain robust.

Finally, the net effect turns out to be an increase in total loans. Such an increase is smaller than the increase in real estate loans due to the decrease in commercial lending. Our findings indicate that big natural hazards have long-term impact on bank asset structure, and small banks are more sensitive to adverse events than large banks, possibly because they have less diversification choices than large banks such as geographical diversification documented in Cortés and Strahan (2017).⁶

In the next section, we provide a theoretical model to explain our two main empirical findings. First, our model captures the fact that disasters stimulate communities' demand for loans for reconstruction by destroying capital. Therefore, banks extend credit and meanwhile sell government bonds to finance such a increase in demand. Second, by assuming that disasters lead to more defaults of commercial loans than real estate and consumer loans, our model explains why real estate lending increases yet commercial lending decreases after natural disasters.

⁶We try different event windows in the Internet Appendix. As we extend the event window, the negative coefficient on commercial loans and positive coefficient on consumer loans become more significant.

Table 3.2: DID Results on the Impact of Disasters on Asset Quantities and Prices: ± 1 Year Event Window

This table presents our baseline results of DID analysis on the impact of natural disasters on assets at the bank level using a ± 1 year event window. We include 86 disasters whose cost are at the top 5% based on the EM-DAT database. We analyze balance sheet values (in million dollars) of real estate loans (denoted by RS Loan), commercial and industrial loans (CI Loan), consumer loans (CS Loan), government securities, and total loans. We define a county within 200km radius of the disaster center as the affected county and a county located between 300km and 400km radius as the unaffected county. We include county and time fixed effects to account for regional and macroeconomic conditions. Standard errors are reported in the parentheses. ***, **, * denote significance level at 1%, 5% and 10% respectively.

	RS Loan			CI Loan			CS Loan			Government Security			Total Loan		
	Small	Large		Small	Large		Small	Large		Small	Large		Small	Large	
Affected $\times$ Post	0.961*** (0.092)	2.710** (1.110)		-0.058 (0.038)	-0.307 (0.589)		0.015 (0.026)	-0.323 (0.578)		-0.227*** (0.058)	-1.025*** (0.378)		0.438*** (0.090)	1.027 (1.066)	
Size	0.458*** (0.002)	0.430*** (0.001)		0.092*** (0.001)	0.119*** (0.000)		0.042*** (0.001)	0.041*** (0.000)		0.086*** (0.001)	0.041*** (0.000)		0.631*** (0.002)	0.616*** (0.000667)	
Capital Adequacy	-11.18*** (0.515)	-342.6*** (12.87)		-1.643*** (0.212)	-16.19** (6.836)		-3.112*** (0.145)	93.38*** (6.703)		1.173*** (0.328)	-3.290 (4.386)		-16.71*** (0.508)	-225.1*** (12.37)	
Liquidity	-14.15*** (1.038)	-573.4*** (23.58)		-2.933*** (0.427)	31.35*** (12.52)		2.133*** (0.293)	0.0634 (12.28)		-1.549** (0.660)	80.27*** (8.036)		-17.99*** (1.022)	-475.3*** (22.66)	
County FE	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Time FE	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Banks	2,319	3,555		2,319	3,555		2,319	3,555		2,319	3,555		2,319	3,555	
Affected Banks	1,508	2,422		1,508	2,422		1,508	2,422		1,508	2,422		1,508	2,422	
R-squared	0.650	0.845		0.333	0.600		0.264	0.188		0.203	0.323		0.772	0.923	
Observations	51,890	79,281		51,890	79,281		51,890	79,281		51,890	79,281		51,890	79,281	

Table 3.3: DID Results on the Impact of Disasters on Asset Quantities and Prices: ± 3 Year Event Window

This table presents our baseline results of DID analysis on the impact of natural disasters on assets at the bank level using a ± 3 year event window. We include 86 disasters whose cost are at the top 5% based on the EM-DAT database. We analyze balance sheet values (in million dollars) of real estate loans (denoted by RS Loan), commercial and industrial loans (CI Loan), consumer loans (CS Loan), government securities, and total loans. We define a county within 200km radius of the disaster center as the affected county and a county located between 300km and 400km radius as the unaffected county. We include county and time fixed effects to account for regional and macroeconomic conditions. Standard errors are reported in the parentheses. ***, **, * denote significance level at 1%, 5% and 10% respectively.

	RS Loan			CI Loan			CS Loan			Government Security			Total Loan		
	Small	Large		Small	Large		Small	Large		Small	Large		Small	Large	
Affected $\times$ Post	0.919*** (0.057)	4.394*** (0.718)		-0.0553** (0.024)	-0.625* (0.361)		0.051*** (0.016)	0.177 (0.412)		-0.257*** (0.036)	-1.626*** (0.242)		0.339*** (0.056)	2.694*** (0.665)	
Size	0.460*** (0.001)	0.431*** (0.000)		0.093*** (0.000)	0.121*** (0.000)		0.043*** (0.000)	0.044*** (0.000)		0.086*** (0.001)	0.043*** (0.000)		0.634*** (0.001)	0.621*** (0.000)	
Capital Adequacy	-11.25*** (0.300)	-331.9*** (8.146)		-1.837*** (0.124)	-11.63*** (4.092)		-3.047*** (0.083)	97.21*** (4.675)		0.651*** (0.190)	0.447 (2.742)		-17.18*** (0.295)	-198.2*** (7.549)	
Liquidity	-14.50*** (0.627)	-603.5*** (15.17)		-2.557*** (0.259)	42.25*** (7.618)		2.561*** (0.173)	0.665 (8.705)		-1.904*** (0.396)	89.00*** (5.106)		-17.68*** (0.615)	-506.2*** (14.06)	
County FE	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Time FE	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Banks	2,532	3,812		2,532	3,812		2,532	3,812		2,532	3,812		2,532	3,812	
Affected Banks	1,660	2,665		1,660	2,665		1,660	2,665		1,660	2,665		1,660	2,665	
R-squared	0.652	0.840		0.329	0.626		0.270	0.165		0.206	0.329		0.776	0.926	
Observations	144,495	216,416		144,495	216,416		144,495	216,416		144,495	216,416		144,495	216,416	

3.4 Theoretical Model

In this section, we first set up a theoretical model to explain banks' asset allocation behavior during disastrous times. Next we calibrate the parameters and compare key financial ratios implied by the model with real data.

We begin with a single asset model so as to introduce our main variables and to show how banks make lending decisions based on loan conditions, e.g. non-repayment rate, disaster probability, and interest rate (model 1). Next, we allow for multiple assets, which enables us to generate interactions among assets when a disaster realizes (model 2). Our model contains two economic players, the banks and the firms that represent the supply and demand side of funds. As will see, firms as a whole determines the basic borrowing interest rate through production and investment. Individual banks then decide how much to lend based on the given interest rate. A disaster destroys firms' capital, increasing the demand for loans, the borrowing interest rate, and possibly the non-repayment rates of existing loans. Individual banks aiming at maximizing shareholder value react to this shock by adjusting their asset structure. The single asset banking model is mainly based on the model of Collier (2014). The production sector and multiple-asset setting are new features.

3.4.1 Model Setup

Bank with a Single Asset

Consider a risk-neutral bank that maximizes its shareholder value over an infinite horizon. Every period, the bank generates new aggregated loans L_t , but only a fraction, $\tilde{L}_t$, are paid back at the end of the period due to default.⁷ We model such a relationship as:

$$\tilde{L}_t = (1 - \xi_t)L_t, \quad (3.2)$$

where ξ_t is the non-repayment rate that is affected by various types of shocks, including natural disasters. It is specified as:

$$\xi_t = \bar{\xi} + \epsilon_t^\xi, \quad (3.3)$$

⁷Since L_t is the stock variable, it would be more precise to include a motion equation, $L_{t+1} = L_t + l_t$, where l_t is the newly issued loans, a flow variable. It represents how much new loans the bank decides to issue every period. However, it is in fact equivalent to say that the bank decides how much loan L_t to have every period. The model will produce exactly the same result whether we specify the motion equation or not. More importantly, since our empirical analysis tests the stock, not flow, of loans, letting the bank to decide the level of L_t makes the theory consistent with the empirical analysis.

where ϵ_t^ξ captures unexpected shocks and $\bar{\xi}$ represents the bank's expected non-repayment rate:

$$\bar{\xi} = p(\alpha + \xi^*) + (1 - p)\alpha = \alpha + p\xi^*, \quad (3.4)$$

where μ represents the non-repayment rate in normal times, ξ^* is the average non-repayment rate increment when a disaster happens, and the bank expects the disaster to happen ($x_t=1$) with a probability p . As will be seen in the next section, we simulate different scenarios of climate change using different values of disaster probability p . A higher disaster probability means higher expected non-repayment rate.

The net income, R_t , is the interest income of performing loans, $r_t\tilde{L}_t$ less the deposit interest payment, $r_t^D D_t$, the origination costs for new loans $h(l_t)$, and the loan losses $\xi_t L_t$:

$$R_t = r_t\tilde{L}_t - r_t^D D_t - h(L_t) - \xi_t L_t, \quad (3.5)$$

where r_t and r_t^D are the interest rates on loans and deposits respectively. We specify r_t as:

$$r_t = r_t^* + \kappa, \quad (3.6)$$

where r_t^* is the equilibrium basic lending rate determined by firms, as will be explained later and κ is the risk premium of the loan. In Collier (2014)'s model, the basic borrowing/lending interest rate r_t is a given parameter. In our model, however, we let it to be determined by the production sector. By destroying capital, natural disasters increase the loan demand as well as the interest rate. Banks then make decisions based on the changed conditions of the economy. This improvement makes our mechanism more elaborate and realistic.⁸

We relate deposit D_t to the interest rate r_t^D and a constant N that controls the size of the balance sheet:⁹

$$D_t = N(1 + r_t^D) \quad (3.7)$$

⁸From an empiricist's point of view, interest rate is persistent. Especially for loans, both banks and customers can not change the rate whenever they want, so the interest rate in the next period is highly correlated with the rate of the last period. This calls for a more realistic interest rate process, for example, $r_t = \rho r_{t-1} + (1 - \rho)\bar{r}_t + \epsilon_t^r$, where ρ represents the persistence of the interest rate and $\epsilon_t^r \sim N(0, \sigma^2)$ is a random shock. In the later simulation part, to conform to reality and also to improve the readability of graphs, we set $\rho > 0$, which means banks continue to charge a higher interest rate some quarters after the disaster.

⁹This is also an extension compared to Collier (2014)'s model that simply set deposit to be the difference between asset and equity. In this way, we can add a shock to the deposit when we have reasons to believe that households and banks react to disasters by withdrawing deposit or changing deposit rate. We did not do this experiment, however, for two reasons. First, we want to focus on the topic of banks' asset allocation rather than how banks adjust their deposit rate. Dlugosz et al. (2017) study in detail how banks' decision-making delegation affect their ability

Consequently, the total loans that the bank can generate is constrained by the balance sheet identity:

$$L_t = D_t + E_t \quad (3.8)$$

As a bank generates more loans, it faces origination costs associated with searching, evaluating, and monitoring borrowers as well as more severe regulation on leverage from authorities. A convenient cost function is:

$$h(L_t) = \eta L_t + \frac{\psi}{2} L_t^2, \quad (3.9)$$

where the linear component implies that origination costs are proportional to the amount of loans, whereas the quadratic part captures the fact that for a bank that already has issued a lot of loans, it becomes more difficult to search, evaluate, and monitor new borrowers and meets increasingly invasive interventions from the banking authorities when its leverage becomes too high.¹⁰ The next period's equity is the current equity less dividend payment plus the income:

$$E_{t+1} = (1 - \nu)E_t + R_t, \quad (3.10)$$

where ν is the dividend rate. Finally, the banks problem is maximizing its overall dividend payment discounted by a time discount factor γ :

$$\max_{L_t} \Pi_0 = \sum_{t=0}^{\infty} \gamma^t \mathbb{E}[\nu E_t], \quad 0 < \gamma < 1. \quad (3.11)$$

To complete the model, we need to introduce the demand side for loans, that is the production sector. Especially, we will treat the firms as a whole so that the society's basic borrowing/lending interest rate is decided by firms' production and investment decisions.

Firms

As disasters affect the whole local economy, we should consider both the financial and non-financial sectors. We will let firms as a whole determine the basic borrowing interest rate through production and investment; individual banks then decide how much to lend based on the given interest rate. We model firms based on a

to set deposit rate and the consequence of deposit level and economic recovery. Second, we did not find robustly significant empirical evidence on the change of deposit after disasters.

¹⁰In Collier (2014), the author explicitly models the regulation cost as a step function that stays at zero when the leverage is low and increases when the leverage exceeds the regulation threshold. We smooth this process in this specification as the kinked function complicates the computation and is not important to our model's main mechanism.

business cycle model of Gourio (2012); they produce output using a Cobb-Douglas production function:

$$Y_t = AK_t^\alpha, \quad (3.12)$$

where A is productivity level, also known as the total factor productivity (TFP). Capital is accumulated according to Equation of motion for production capital:

$$K_{t+1} = (1 - \delta_t)K_t + \phi\left(\frac{I_t}{K_t}\right)K_t, \quad (3.13)$$

where δ_t is the depreciation shock, I_t is the demand for funds, and $\phi\left(\frac{I_t}{K_t}\right)$ is a function of capital adjustment cost.¹¹ Here comes the role of disaster: it increases the capital depreciation rate:

$$\delta_t = \bar{\delta} + \epsilon_t^\delta. \quad (3.14)$$

If ϵ_t^δ and ϵ_t^ξ are positively correlated, then this means disasters indeed lead to default of existing loans. Finally, firms maximizing profit over time according to:

$$\max_{I_t, K_{t+1}} \Pi_0^{Firm} = \sum_{t=0}^{\infty} \beta^t \mathbb{E}[Y_t - I_t - r_t^* K_t], \quad 0 < \beta < 1, \quad (3.15)$$

where β is the time discount factor for firms. Through the production and investment decisions, firms determine the basic borrowing interest rate:

$$1 + r_t^* = \phi'\left(\frac{I_t}{K_t}\right) \left(\frac{1 - \delta_t + \phi\left(\frac{I_{t+1}}{K_{t+1}}\right)}{\phi'\left(\frac{I_{t+1}}{K_{t+1}}\right)} + \alpha \frac{Y_{t+1}}{K_{t+1}} - \frac{I_{t+1}}{K_{t+1}} \right). \quad (3.16)$$

To sum up the mechanism, disasters increase the depreciation rate of firm capital, drives up interest rate, affect the non-repayment rate, and eventually lead banks to adjust their capital structure. By now, the model still cannot explain the interactions among assets during disastrous period. We therefore make a small extension to incorporate multiple assets.

Bank with Multiple Assets

Having established the single-asset model, we slightly enrich the model to allow for interactions among multiple assets.¹² Each asset has its own non-repayment rate (zero for government bonds), interest rate, and cost function.

¹¹Follow the convention of business cycle literature, we specify the capital adjustment function to be $\phi\left(\frac{I_t}{K_t}\right) = \frac{I_t}{K_t} - \frac{\iota}{2} \left(\frac{I_t}{K_t} - \delta\right)^2$. It is therefore an increasing and concave function.

¹²In the quantitative analysis, we looked at four distinct asset classes, i.e. loans secured by real estate, commercial and industrial loans, consumer loans, and government securities.

The net income include the sum of interest income of all assets:

$$R_t = \sum_{i=1}^n r_i \tilde{L}_{it} - r_t^D D - h(L_t) - \sum_{i=1}^n \xi_{it} L_{it}, \quad (3.17)$$

where i indexes the asset class and n is the number of assets. and

$$r_{i,t} = r_t^* + \kappa_i, \quad (3.18)$$

where the bank's average lending rate $\bar{r}_{it}$ for asset i is the sum of the basic borrowing/lending rate r_t^* and the risk premium κ_i of that asset.

The total cost is the sum of individual cost:

$$h(L_t) = \sum_{i=1}^n \eta_i L_{it} + \frac{\psi_i}{2} L_{it}^2. \quad (3.19)$$

Finally, the balance sheet identity becomes:

$$\sum_{i=1}^n L_{it} = D_t + E_t. \quad (3.20)$$

Despite the simple changes, model 2 can now capture the important trade-off among assets. In the following two propositions, we first look at the impact of the interest rate on the level of total loans and then illustrate the trade-off property using two assets.

3.4.2 Static Analysis

Proposition 1: The level of total loans increases with the interest rate and decreases with the non-repayment rate and disaster probability.

Proof: At the steady state, the level of aggregated loans L is a constant and the interest rate and non-repayment rate equal to their mean values $\bar{r}$ and $\bar{\xi}$. Solving the steady states of model 1, we find:

$$L = \frac{[(1 - \bar{\xi})\bar{r} - \eta - \bar{\xi} - \nu] + \sqrt{[(1 - \bar{\xi})\bar{r} - \eta - \bar{\xi} - \nu]^2 - 2\psi(\bar{r}^D - \nu)\bar{D}}}{\psi}. \quad (3.21)$$

After taking the first derivatives, we have $\frac{\partial L}{\partial \bar{r}} > 0$, $\frac{\partial L}{\partial \bar{\xi}} < 0$, and $\frac{\partial L}{\partial \nu} < 0$. Therefore, the amount of loans is positively related to the interest rate and negatively related to the non-repayment rate. More detailed derivations are shown in our Internet Appendix.

This proposition is straightforward. The first part follows the law of demand and supply. As for the second part, when banks face higher default risks, thus a

higher non-repayment rate or a higher disaster probability, to guarantee a stable income and shareholder value, banks tend to be more prudent in issuing loans.

Proposition 2: Suppose a bank has two assets. When one asset has an increase in interest rate, the bank will increase the holding of this asset and decrease the holding of another one.

Proof: Solving the steady states of model 2, we find:

$$L_1 = \frac{[(1 - \bar{\xi}_1)r_1 - \eta_1 - \bar{\xi}_1] - [(1 - \bar{\xi}_2)r_2 - \eta_2 - \bar{\xi}_2] + \psi_2(D + E)}{\psi_1 + \psi_2}. \quad (3.22)$$

So the level of one asset is positively related to its own interest rate but is negatively related to the interest rate of another asset. That is $\frac{\partial L_1}{\partial \bar{r}_1} > 0$ while $\frac{\partial L_1}{\partial \bar{r}_2} < 0$. Therefore, when a disaster increases the demand and the interest rate of one asset, facing the budget constraint, the bank will decrease the holding of another asset. We put detailed derivations in our Internet Appendix.

In the following analysis, we will calibrate our model parameters and illustrate these two propositions more vividly with impulse response graphs.

3.4.3 Calibration

In this subsection, we calibrate the model using quarterly data for commercial banks. Some values are calculated direct from real data; others are chosen such that the steady-state values of our key financial variables match the average data statistics. Table 3.4 summarizes the calibrated parameters for our two models.

The non-repayment rate of an outstanding loan equals one less the loan's net loss rate. For each type of loan, the net loss is reported in the UBPR as year-to-date (YTD) net loss.¹³ In our calibration, we use one minus the mean of a loan's net loss divided by the notional amount as the expected value of the non-repayment rate ($\bar{\xi}$). We manually assign the non-repayment rate of government securities to be zero.

The time discount factor for banks and firms, γ and β , are both set to be 0.95, which is a standard value used in the literature. To determine the risk premium for each bank asset, we first take the average of each asset's interest rates over time and across states and use this value as the interest rate (name it as $\bar{r}_i$) of this asset. As at the equilibrium, the basic borrowing rate determined by firms

¹³The UBPR codes for the total loan, real estate loan, C&I loan, and the consumer loan are UBPS019, UBPS397, UBPS408, and UBPS410 respectively. Since the "year-to-date net loss" refers to the cumulative loss so far this year, to calculate the quarterly net loss of a loan, we need to subtract the value of the YTD net loss in the current quarter by the value of the YTD net loss in the last quarter.

is simply $r^* = 1/\beta - (1 - \bar{\delta})$, we calibrate the risk premium for each asset as $\kappa = \bar{r}_i - (1/\beta - (1 - \bar{\delta}))$. The data is from the UBPR.

The cost parameters are chosen to match certain financial ratios between our model and the data, as can be seen in the next subsection. Other parameters are calibrated to match the ratios of key variables as shown in the next subsection. For example, the scale constant N determines the level of deposits and therefore the size of the balance sheet. The dividend rate is based on the return on average equity for all U.S. banks from the Federal Reserve Bank of St. Louis.

Table 3.4 shows that real estate loans have the highest credit quality among the three types of loans, as indicated by its lowest average non-repayment rate compared to other loans. The value means that every quarter, the default rate for real estate loans is around 1%. The commercial and industrial loans have the lowest credit quality with an average non-repayment rate of 3%. This difference reflects the role of collateral in promoting the timely non-repayment of loans and validates why real estate lending is the biggest lending business of banks (Gan, 2007; Chaney et al., 2012). Having these calibrated parameters in hand, we show our model can generate key financial ratios that are close to real data.

In this subsection, we examine the model's quantitative performance. We first compare some key financial ratios generated by the model with ratios based on real data. Next, we carry out simulations to examine the effects of changes in asset prices after disasters.

3.4.4 Data versus Model Moments

In Table 3.5, we show the statistics of key financial ratios. The left panel shows ratios calculated based on the call report data of U.S. commercial banks. To avoid extreme values caused by the size factor, we select banks with total assets between the 25th and 75th quantiles. Ratios in the right panel are based on model simulation. The simulated values are the average statistics derived from a Monte Carlo simulation by drawing from the capital depreciation shock (ϵ_t^δ) distribution. Each of the 5,000 simulations has 45 observations as our real data covers 45 quarters. The mean and median of the capital ratio indicated by the real data are 10.7% and 9.9% respectively. For the simulated capital ratio, the mean value is 9.4% in model 1 and 11.3% in model 2; both are reasonable values compared to the real data. The table shows that except for the capital ratio, other financial ratios vary greatly across banks, which confirms the diversity of bank business mode. Given the huge deviations in the real data, the ratios generated by our model are all in the reasonable domain.

Table 3.4: Calibrated Parameters

This table reports our calibrated parameters. The interest rate premium and components of non-repayment rates are based on the average interest rate and non-repayment rate reported in the Uniform Bank Performance Report (UBPR). We have data on real estate loans (labeled as RS), commercial and industrial loans (CI), and consumer loans (CS). Since the net losses data for the government securities are not available, we set the nonrepayment rate of government securities (GS) to be zero. We fix the interest rates on deposit and government bond and let the interest rates of other assets to be the sum of the basic equilibrium rate and their corresponding risk premium. Parameters that cannot directly be calculated from the data are calibrated to match the data moments such as the capital ratio and the relative ratios among different assets.

Concept	Symbol	Model 1	Model 2				Calibration Method
		Total Loans	RS	CI	CS	GS	
Normal time non-repayment rate (%)	μ	2	0.5	2	3	0	match UBPR data
Disaster time non-repayment rate (%)	ξ^*	1	2	2	2	0	match UBPR data
Mean interest rate (%)	$\bar{r}$	6.78	6.65	6.93	8.14	3.39	interest rate data from UBPR
Risk premium (%)	κ	1.52	1.39	1.67	2.88	-	$\kappa = \bar{r} - (1/\beta - (1 - \bar{\delta}))$
Cost (linear component) (%)	η	1	0.5	0.1	0.1	0.5	match data moments
Cost (quadratic component) (%)	ψ	0.01	0.2	0.5	0.7	0.5	match data moments
Time preference bank	γ	0.95		0.95			standard value
Scale constant of deposit	N	20		20			match data moments
Dividend rate (%)	ν	15		15			average ROE for all U.S. Banks from Federal Reserve Bank of St. Louis
Deposit interest rate (%)	r^D	2.02		2.02			interest rate data from UBPR
Persistence of interest rate (%)	ρ	0.4		0.4			standard value
Time preference firm	β	0.95		0.95			standard value
Total factor productivity	A	1		1			a scale constant; value does not affect the results
Capital share	α	0.33		0.33			standard value
Depreciation rate (%)	δ	2		2			standard value for quarterly depreciation rate

Table 3.5: Statistical Moments: Data vs. Model

This table shows the statistical moments based on the real data and the simulated values of the models. The data are from the Call Reports with time horizon from 2002 to 2013. To avoid extreme values caused by the size factor, we select banks with total assets between the 25th and 75th quantiles and calculate the means, medians, and standard deviations of financial ratios of interest. On the left panel, simulated values are the average statistics derived from a Monte Carlo simulation based on the shock distribution of the capital depreciation rate. We set the standard deviation of ϵ_t^δ to be 0.01, which is almost a 50% variation compared to the mean value of δ , which is 0.02. As our real data covers 45 quarters, we let each of our 5,000 simulations to have 45 observations.

	Data			Model		
	Mean	Median	Std.Dev	Mean	Median	Std.Dev
				Model 1		
Equity/Total Loans	0.107	0.099	0.042	0.094	0.093	0.017
Equity/Deposit	0.527	0.141	33.199	0.101	0.100	0.020
				Model 2		
Equity/Total Loans	0.107	0.099	0.042	0.113	0.113	0.013
Equity/Deposit	0.527	0.141	33.199	0.125	0.125	0.016
Loan CI/loan RS	0.317	0.188	5.022	0.275	0.275	0.119
Loan HH/loan RS	0.235	0.078	7.933	0.206	0.206	0.086
Gov. securities/loan RS	0.296	0.115	2.308	0.050	0.050	0.045

To further reduce the concern that the previous simulated financial ratios are sensitive to parameter values we choose, we perform a sensitivity test. In particular, we select some parameters that cannot be directly inferred from real data and therefore may suffer from our subjective arbitrariness. These parameters include the components in the cost function (η and ψ), the time preferences of bank and firm (γ and β), and the constant scale parameter N that determines the size of the balance sheet. We increase or decrease them by 10% respectively and compare the key financial ratios with the medians of the baseline model and real data. Our results in Table 3.6 show that the simulated moments are not sensitive to the parameter we use. Except for the ratio of government bond to real estate loan, which has a drop of 7% compared to the baseline simulation but still within the reasonable domain compared to real data, other ratios change only slightly.¹⁴

Up to this point, we have set up our model, derived its static implications, and calibrated the model to match the real bank data. To see how our model can justify banks' dynamic asset adjustment behavior found in our empirical analysis, we simulate a realization of natural hazard in the next section.

¹⁴Since in model 2, cost parameters η and ψ are vectors, one may want to change values for each individual element rather than uniformly increase or decrease values by 10%. We did try 10% deviation for each individual element and the results remain robust.

Table 3.6: Sensitivity Test of Model Parameters

This table presents results of the sensitivity test of selected model parameters. We choose parameters that cannot be directly inferred from real data as they may suffer from some subjective arbitrariness. These parameters include η , ψ , γ , N and β . We increase or decrease them by 10% and compare the key financial ratios with the medians of the baseline model and real data.

	Data	Baseline	Parameter +10%	Parameter -10%
Equity/Total Loans	0.099	0.093	0.084	0.102
Equity/Deposit	0.141	0.100	0.089	0.111
Equity/Total Loans	0.099	0.113	0.091	0.132
Equity/Deposit	0.141	0.126	0.099	0.149
Loan CI/loan RS	0.188	0.272	0.295	0.252
Loan HH/loan RS	0.078	0.205	0.220	0.191
Gov. securities/loan RS	0.115	0.093	0.069	0.029

3.5 Simulation of Disaster

In this part, we simulate the demand-driving effect of a natural disaster. Specifically, the disaster destroys production capital, stimulates demand for loans; the interest rate then increases as a result of the reduced capital stock and increased investment need. We explore how these changes can affect a bank's asset allocation. In both model 1 and model 2, we simulate a 1% increase in the capital depreciation rate. We use 1% change in the capital depreciation rate as an example because the quarterly capital depreciation rate is 2% according to the literature (Bachmann et al., 2013); therefore, 1% can proxy a large shock induced by a rare disaster, as studied in our empirical analysis. Our model in this study provides one explanation among many about banks' asset allocation behavior; we do not, however, intend to match every simulated number exactly with the empirical findings.

For model 1, as shown by Figure 3.4, capital level drops after a disaster. Firms thus need more investment to recover production, so the lending rate increases. In response to these changes, the bank increases its origination of total loans by about 0.8% (the red curve). As a result, the bank earns more interest income and increases its equity level by about 8%. Further, the bank boosts its capital adequacy by more than 0.5%. In brief, as the bank extends its credit, our model implies a positive role of commercial banks in supporting the economic recovery. In another case, we let the depreciation rate and the non-repayment rate to be correlated. That is, a disaster destroys firm capital, interrupts production, and leads to delayed loan payment or even default. If we assume that a 1% increase in depreciation rate is associated with a 0.5% increase in the non-repayment rate, then as indicated by the green curves, banks will have few new loans generated

Figure 3.4: Effects of a 1% Increase in the Capital Depreciation Rate on Loan Origination, Equity, Capital Ratio (or Equity Ratio), and Income (Model 1). This figure shows the percentage deviations of loans, equity, income, firm capital, and interest rate from their steady states and the change in the capital ratio if the capital depreciation rate δ increase by 1% after a disaster based on model 1. The green lines represent the case when the depreciation rate and non-repayment rate ξ are correlated; we assume that a 1% increase in depreciation rate is associated with a 0.5% increase in the non-repayment rate. The previous five periods (i.e. -5 to -1) are interpolated as peaceful periods to improve the readability of the figure.

and all other variables increase to a less amount compared to the previous case.

Figure 3.5 shows the effects of a disaster on different assets based on model 2. The impact of the disaster on the production sector is the same as model 1. The difference is that, when we consider multiple assets, we see the bank increases the origination of all types of loans as interest rates increase, but at the same time decrease the holdings of government bonds. Specifically, our model implies a roughly 4% increase in every type of loan and a 60% decrease in the government securities. Comparing with the empirical findings. Our model is consistent with the findings of the increased real estate and consumer loans and decreased government securities.

There are, however, two differences. The first is related to the change of commercial loans. As is indicated by our empirical finding, banks decrease the

origination of commercial loans after disasters whereas the simulation here implies an increase. This is because for simplicity, we do not consider the correlation between depreciation rate and non-repayment rate. As commercial loan is riskier than real estate loan and can be more prone to disaster-related default, the non-repayment rate may increase after disasters. We show in the Internet Appendix that, when a 1% increase in the capital depreciation rate is associated with 0.5% increase in the non-repayment rate in the commercial loan, then both the direction and magnitude of the changes in loans are in line with our empirical findings. The second difference concerns the magnitude of the change in government bonds. The simulation implies a quite large (60%) drop while the empirical findings reveal the drop to be around 4%. As we have stated, in this study, we highlight banks using of the internal asset diversification strategy in response to disasters. Banks of course can have many other solutions to endure disaster. In the previous research, Cortés and Strahan (2017) have shown that banks adjust lending between affected and unaffected regions. If banks use many strategies to cope with disasters, then the drop in the holdings of government bonds can be smaller.

In short, with a dynamic multiple-asset credit rationing model, we can explain why and how banks adjust their asset structure in response to natural hazards. By strategically (re)allocate assets, banks not only meet the need of the increased loan demand of the community, but also guarantee a stable income and shareholder value for themselves. In the next section, we go a step further by looking at the impact of climate change on banks' asset structure.

3.6 *Does Climate Change Affect Banks' Asset Structure?*

Besides explaining banks' credit rationing behavior immediately after disasters, our model can also show long-run implications on banks' asset structure due to climate change. As has been predicted by the Intergovernmental Panel on Climate Change (IPCC), global warming can increase the chance of natural hazards, especially floods and hurricanes that accounts for a large portion of the disaster sample in our empirical analysis (Pachauri et al., 2014). Therefore, we simulate four scenarios of permanent changes of disaster probability, i.e. +10%, +5%, -5%, and -10%. The increased probability scenarios are based on the prediction that climate change can increase the chance of natural disasters. We also show scenarios of decreased probability to compare them with the implications of climate change.

As shown in Figure 3.6, consistent with Proposition 1 in our static analysis, model 1 implies that an increase in disaster probability leads to decreased loan

Figure 3.5: Effects of a 1% Increase in the Capital Depreciation Rate on Bank Assets, Equity, Capital Ratio, and Income (Model 2). This figure shows the percentage deviations of bank assets and income from their steady states if the capital depreciation rate δ increase by 1% after a disaster based on model 2. The abbreviations RS, CI, and CS mean real estate loans, commercial and industrial loans, and consumer loans. The previous five periods (i.e. -5 to -1) are interpolated as peaceful periods to improve the readability of the figure.

Figure 3.6: Effects of Different Permanent Shocks to Disaster Probability. In this figure, we assume four different scenarios about the change of disaster probability. We assume permanent changes of quarterly disaster probability to be +10%, +5%, -5%, and -10% respectively. We have scenarios of increased probability because climate change can increase the chance of natural disasters. We also show scenarios of decreased probability to compare them with the implications of climate change.

origination, income, equity. This is because higher disaster probability means higher expected non-repayment rate and lower income and shareholder value. As a result, banks generate less credit. Beside, since equity decreases more than loans, the capital ratio also decreases. Therefore, our model implies that climate change not only reduces banks' ability of issuing credit, but also affects banks' stability by letting banks to maintain less capital.

As for model 2, consistent with Proposition 1, Figure 3.7 shows that higher disaster probability leads to a lower level of all types of loans. However, in line with Proposition 2, banks increase the holdings of government bonds. This is because government bonds have zero non-repayment rate and are therefore a safer asset compared to loans. Similar to the prediction of model 1, in model 2, banks' income, equity, and capital ratio also decrease.

To sum up, by assuming different changes in disaster probability due to climate change, our model implies that climate change hinders banks' capacity of issuing credit and reduces banks' capital adequacy. These changes are apparently not good for investment and banks' own stability.

Figure 3.7: Effects of Different Permanent Shocks to Disaster Probability. In this figure, we assume four different scenarios about the change of disaster probability. We assume permanent changes of quarterly disaster probability to be +10%, +5%, -5%, and -10% respectively. We have scenarios of increased probability because climate change can increase the chance of natural disasters. We also show scenarios of decreased probability to compare them with the implications of climate change.

3.7 Conclusion

This paper examines how banks strategically reallocate their assets when natural disasters stimulate demand for loans found in previous literature. In the empirical analysis, we find that natural disaster affect banks' asset structure. The changes are both statistically and economically significant. Specifically, banks increase loans secured by real estate by about and sell government securities to finance the increased demand for credit. Further, small banks have bigger fluctuations in the level of assets than large banks after disaster, which is due to tighter budget constraint or less flexibility of diversifying assets internally.

In the theoretical part, we develop a multiple-asset dynamic credit rationing model to explain our main empirical findings. Our model includes both the supply and demand sides. It captures banks' asset allocation behavior found in the empirical analysis and has further implications on climate change. To the best of our knowledge, there has not yet been either empirical or theoretical papers showing the interaction among different assets. We therefore make a contribution to the credit rationing literature on both the empirical and theoretical aspects.

Appendix

Table 3.7: Terminology

This table presents definitions of all the terminologies related to natural disasters and banking variables used through out the paper as well as their abbreviations. The definitions of the banking variables can be found in the instructions of the Call Reports compiled by the Federal Deposit Insurance Corporation (FDIC).

Natural disaster	A natural disaster is a major adverse event resulting from natural processes of the Earth; examples include floods, volcanic eruptions, earthquakes, tsunamis, and other geologic processes. A natural disaster can cause loss of life or property damage, and typically leaves some economic damage in its wake, the severity of which depends on the affected population's resilience, or ability to recover. ¹
Loans secured by real estate (RS)	A loan secured by real estate is a loan that, at origination, is secured wholly or substantially by a lien or liens on real property for which the lien or liens are central to the extension of the credit – that is, the borrower would not have been extended credit in the same amount or on terms as favorable without the lien or liens on real property.
Commercial and industrial loans (CI)	Loans for commercial and industrial purposes to sole proprietorships, partnerships, corporations, and other business enterprises, whether secured (other than those that meet the definition of a “loan secured by real estate”) or unsecured, single-nonrepayment or instalment. ²
Consumer loans (CS)	In this category, a bank will report all its credit extended to individual for household, family, and other personal expenditures that does not meet the definition of the loans secured by real estate. It includes credit cards, other revolving credit plans, automobile loans, and other consumer loans.
Government securities (GS)	This variable is a combination of two categories in the call report: 1) U.S. Treasury securities: amortized cost and fair value of all U.S. Treasury securities not held in trading accounts. It should include all bills, certificates of indebtedness, notes, and bonds. 2) U.S. Government agency obligations: the amortized cost and fair value of all U.S. Government agency obligations not held for trading. But the mortgage-backed securities are excluded. ³
Interest-bearing deposits (DP)	Interest-bearing deposits accounts consist of deposits accounts on which the issuing depository institution makes any nonrepayment to or for the account of any depositor as compensation for the use of funds constituting a deposits.
Loans Net Losses (%)	The year-to-date net loss (change offs less recoveries) for the gross (or a specific type of) loans divided by average gross (or a specific type of) loans. ⁴

¹ This definition is from Wikipedia-Natural Disaster.

² The Loan and Lease part, schedule RC-C has two parts, the second of which is “Loans to Small Businesses and Small Farms”. But the first part already includes the second part.

³ The definitions of the above bank assets are from each individual schedules of the *Reports of Condition and Income Instruction Book (Updated June 2015)*.

⁴ Year-to-date (YTD) net loss refers to the loss so far this year. To calculate the net loss in the 3rd quarter, we need to subtract the value of 3rd quarter YTD net loss by the value of 2nd quarter YTD net loss.

Figure 3.8: Interest Rates on Loans and Securities for Selected States of U.S. This figure shows yields on real estate loans, commercial and industrial loans, consumer loans, government securities, mortgage-backed securities, and deposit at the state level from 2002:Q4 to 2013:Q4. The selected states are Louisiana, Pennsylvania, Florida, and California.

Table 3.8: List of Significant Natural Disasters in the US: 2001 to 2015

Year	State Mainly Affected	Type	Name	Total Damage (Million)
2005-08/09	Louisiana	Tropical storms and cyclones	Hurricane Katrina	125000
2012-10	New York	Tropical storms and cyclones	Hurricane Sandy	80000
2004-08	Florida	Tropical storms and cyclones	2004 Atlantic Hurricane Season; Hurricane Frances, Ivan	18000
2005-09	Louisiana	Tropical storms and cyclones	Hurricane Rita	16000
2004-09	Florida	Tropical storms and cyclones	2004 Atlantic Hurricane Season; Hurricane Frances, Ivan	12000
2008-06	Missouri	Floods	June 2008 Midwest floods	10000
2001-06	Louisiana	Tropical storms and cyclones	2001 Atlantic Hurricane Season; Hurricane Allison	6000
2003-09	North Carolina	Tropical storms and cyclones	Hurricane Isabel	5000
2011-04/05	Arkansas	Floods	2011 Mississippi River Floods	3000
2010-04/05	Tennessee	Floods	2010 Tennessee Floods	2350
2011-05/06	Iowa	Floods	2011 Missouri River Floods	2000
2001-02	Washington	Earthquakes	2001 Nisqually earthquake	2000
2013-09	Colorado	Floods	2013 Colorado floods	900
2011-08	Pennsylvania	Floods	2011 Atlantic Hurricane Season; Tropical Storm Lee	1200
2011-09	Mississippi	Tropical storms and cyclones	2011Atlantic Hurricane Season; Tropical Storm Lee	1000
2006-06	Pennsylvania	Floods	Mid-Atlantic United States flood of 2006	1000
2002-07	Texas	Floods	Late June and Early July Floods of 2002	1000

Towards Good Governance: How Do Institutions Affect the Efficiency of Disaster Relief?

4.1 *Introduction*

Natural disasters become more and more frequent in recent years. Through media coverage, we can strongly perceive that the performance of countries differ greatly during their disaster mitigation. Some countries can quickly mobilize resources to support the affected regions while the others appear very inefficient and suffer more damages in the aftermath. How do countries rank by their disaster-relief performance? Why countries perform so differently? Do political institutions play a role? In this paper, we evaluate countries' disaster-relief efficiency and emphasize the role of good governance in mitigating the disastrous impact.

Specifically, we assemble a unique dataset that provides us with multiple measures of the consequences of disasters for countries worldwide. Next, we evaluate countries' disaster-relief efficiency using an output distance stochastic frontier framework that unifies different measures of disaster damages in a single estimation model. We further provide evidence that countries with better institutional quality on average have higher efficiency. Finally, we show that, by reforming their institutions, countries, especially emerging ones, have increased their resilience in enduring disasters in the past decades.

What are institutions? Following previous studies, we define institutions as “the rules of the game in a society or, more formally, are the humanly devised constraints that shape human interaction” (North, 1990; Acemoglu and Robinson, 2010). Furthermore, in this paper, we treat governance as a part of institutions and use a set of indicators to represent the quality of governance. According to the World Bank, governance consists of “the traditions and institutions by which authority in a country is exercised” (Kaufmann et al., 2010). Our key argument is that, by adopting good governance, countries can improve their efficiencies in disaster mitigation. Here, efficiency reflects how a country is able to keep its actual damage as close as to its minimum unavoidable damage. It is estimated by the stochastic frontier model, which will be detailed in the following analysis.

This chapter is co-authored with Jaap Bos (Maastricht University), Martien Lamers (Groningen University), Mark Sanders (Utrecht University), and Vincent Schippers (Utrecht University). We thank Gabriel Felbermayr and Jasmin Gröschl for providing the GeoMet data.

Through using a stochastic frontier model and considering different measures of disaster damages at the same time, we have made several contributions in understanding the effects of good governance on disaster-relief efficiency. First and foremost, our model offers a benchmark for comparing countries that differ enormously in their economic and natural conditions such as population size, capital stock, and climatological properties. This is because the model controls for those conditions and includes various disaster consequences in an outmost cost frontier. Specifically, in this setting, we will measure the distance between a country's actual disaster cost and its minimum unavoidable damage determined by the country's economic and natural preconditions. Such distance therefore reflects the country's efficiency in mitigating disastrous impact. As a matter of fact, that outmost sphere serves as a benchmark for comparing countries' efficiencies.

We make our second contribution by unifying multiple measures of disaster consequences into a single estimation model. Recent studies on the impact of natural hazards use merely a single variable, such as the drop in the local GDP or the death toll, to represent disaster consequences. (Kahn, 2005; Escaleras et al., 2007; Toya and Skidmore, 2007; Kellenberg and Mobarak, 2008; Cavallo et al., 2011; Kellenberg and Mobarak, 2011; Schumacher and Strobl, 2011; Strobl, 2011). Even though Raschky (2008) and Felbermayr and Gröschl (2014) include multiple measures of physical damages into their data, the authors mainly focus on the disasters' impact on economic growth and thus do not explore the correlation between different measures. We argue that using a model that incorporates several outputs into one equation allows us to gain important additional insights. Interestingly, we find a trade-off between the number of people killed and the economic damage incurred. To be specific, we find that the rise in efficiency implies a decrease in the death toll but an increase in the material damage. Put differently, to be efficient means to be humane in institutions. This is intuitively straightforward: after all, good governance is the art of balancing the trade-offs.

The third contribution relates to the finding that institutional variables, especially those that reflect good governance, positively predict disaster-relief efficiency. This finding points out that, if a country wants to reduce the gap between the minimum and actual losses, reforming its institutional quality is a possible way to achieve that goal.

Our paper has four major findings. First, we show countries differ largely in their disaster-relief efficiencies. During 1996 to 2010, New Zealand on average has performed best in disaster mitigation, followed by other developed nations such as Canada, Japan, and the United States. Developing countries such as China, India, and Brazil usually have a middle rank between 20th and 40th. Second, institutional

variables, especially governance quality indicators, such as government effectiveness, control of corruption, regime durability, voice and accountability, and regulatory quality, promote the efficiency. Specifically, a 0.1 increase in the government effectiveness score leads to a 16% increase in efficiency while a 0.1 improvement in the control of corruption score implies a 40% increase in efficiency. Third, we graphically show that countries actively engaging in reforming their governance in the past years experience increases in their disaster-mitigation efficiencies. Finally, we confirm the trade-off relationship between the human mortality and the economic damage during disaster mitigation. In particular, we show that a 10% increase in efficiency leads to a 11.46% decrease in the number of people killed but a 50.69% increase in the material damage.

Our paper fits within the literature on how political institutions play a role during natural disaster periods (Besley and Burgess, 2002; Garrett and Sobel, 2003; Anbarci et al., 2005; Kahn, 2005; Strömberg, 2007; Kellenberg and Mobarak, 2008). Among them, our paper is most closely related to the seminal work of Kahn (2005) who explores specifically the relationship between governance quality and disaster mitigation. Studying countries worldwide, the author points out that high income as well as good institutions lead to less people killed by natural disasters.

Compared to the work of Kahn (2005), our paper uses a similar set of governance quality indicators, but goes further into three directions. First, we formally measure countries' disaster mitigation efficiencies and rank them based on the same benchmark thanks to the stochastic frontier model. Second, utilizing our newer dataset, we are able to detect the trade-off between the death toll and the economic damage controlling for disaster intensity. Third, we show good governance plays a significant role in shielding people from disasters, whereas democratic level does not, which is contrary to the previous findings. We attribute this finding to our updated data, which reveals that good governance and the conventionally cited democratic score are not necessarily the same thing.

Our study also relates to papers that make the theoretical case for the importance of institutions. For instance, Robinson and Torvik (2005) provide a theory that explains why socially inefficient projects are preferred by some countries. The reasoning is that inefficient projects can be undertaken by a few, but not all, politicians who can therefore make credible promises to their supporters to attract their votes. Acemoglu et al. (2011) use an equilibrium model to explain why inefficient states emerge in some societies and why such inefficient system tends to persist over time. They treat how easily bureaucrats can be monitored by the public as the yardstick for efficiency. Our paper quantifies their definition by em-

playing several institutional variables that reflect public monitoring power. We indeed find that these variables are positively related to the efficiency of disaster mitigation.

Following the theoretical predictions, empirical studies provide more evidence on politician’s characteristics and their behavior in disaster alleviation (Keefer et al., 2011; Neumayer et al., 2014; Botzen et al., 2016). For example, controlling for earthquake propensities, Keefer et al. (2011) find that mortality is higher in autocratic countries where governments have fewer incentives to provide public goods. Botzen et al. (2016) show that after Hurricane Sandy in 2012, Democrats, compared to Republicans, perceived a significantly higher probability of suffering flood damage and they tended to invest in individual flood protection measures. This is why we see that environmental issues account for a more important component of the political agenda of the Democratic Party than of the Republican Party.

In short, by comparing countries’ disaster-relief efficiencies and the role of good governance in promoting efficiencies, our paper contributes to the understanding of how to improve the role of government to better mitigate the impact of natural disasters.

The rest of the paper is organized as follows. Section 4.2 describes the data, visualizes disasters, and summarizes key statistics. Section 4.3 elucidates the empirical method. Section 4.4 presents our main results and discusses robustness checks. Section 4.5 concludes.

4.2 *Data, Descriptive Figures, and Statistics*

We construct our data by merging four datasets. Our dependent variables are disaster damages from the Emergency Events Database (EM-DAT). Our key explanatory variables are institutions. They are mainly the governance quality indicators from the World Bank. Besides, we control for macroeconomic variables from Penn World Table and disaster intensities from the GeoMet dataset compiled by Felbermayr and Gröschl (2014). The time horizon for the disaster data is 1979 to 2010, and the period for the institutional data spans from 1996 to 2010.

4.2.1 *Data for Disasters and Economic Variables*

The EM-DAT data collect the time and geological locations, i.e. latitudes and longitudes, of natural disasters worldwide. Figure 4.1 illustrates the distribution of

Figure 4.1: Disaster Distribution of the World (2006-2010). This map plots geographical locations of all types of disasters worldwide for the period 2006-2010. Marker size and color darkness are both strictly increasing in the human consequences index. The map shows 4304 disaster events during this period. The data are obtained from the EM-DAT database. The background color for each country represents the level of corruption control with lighter colors representing better corruption control. The figure shows that natural disasters are prevalent over the world and the frequency of disasters is not significantly correlated with corruption.

all kinds of natural disasters during 2005 to 2010. The background color represents a country’s strength in controlling corruption. The greener the country is, the less corruption it has. The center of each dot represents the geological location, and the size of each dot is positively related the “human consequences index” provided in the EM-DAT.²

The most important take-away lesson of this figure is that richer nations, usually also less corrupted nations, do not experience fewer disasters or milder shocks than poorer nations, which is in line with the conclusion by Kahn (2005). In the light of this statement, a country’s economic strength and governance quality do play a role in protecting people from hazards. In addition, Figure 4.2 plots the counts of different types of disasters and their continents. It tells us that flood and storm are the biggest threat to human beings, accounting for almost 70% of the total events. Moreover, the lower panel shows that Europe has the highest number of disasters after scaling the continent size, which further excludes the possibility that richer countries are lucky in avoiding disasters or rich because they are spared.

Our second disaster dataset is the GeoMet dataset built by Felbermayr and

²The “human consequences index” takes the values 1 to 5. We could use the number of people killed by disasters as a determinant for disaster severity. However, the mortality number has a huge range, making it difficult to plot. Besides, our purpose for drawing this figure is to show the distribution; detailed numerical analyses are in the Results section.

Figure 4.2: Disaster Distribution by Type and Continent. This bar chart plots the number of each type of disasters taking place in each of the six continents during 1979 to 2010 as well as the number scaled by continent size based on the EM-DAT dataset. The figure shows that floods and storms are the two major disasters to human beings and Europe has the highest number of disasters after scaling the continent size by squared 1000 kilometers.

Gröschl (2014). To measure the physical disaster intensity, the authors collected data primarily from geophysical or meteorological databases, hence the name GeoMet. This new dataset therefore contains disaster-specific intensity measures such as the magnitude of the earthquake, Volcanic Explosive Index, wind speed during storms, and precipitation and temperature when there were floods or droughts. Crucially, as these measures are exogenous to GDP, they facilitate the causality identification for studying the impact of disasters on development. As for this study, we also benefit from these exogenous variables by controlling for them.

Our macroeconomic variables are merged from the Penn World Data (Feenstra et al., 2015). We control for a country’s population density (total population/country area) and capital density (capital stock at current PPPs/country area), because the more dense the people and capital are, the more human and material damage a disaster will incur. We also control for GDP per capita because previous studies has shown that high income could protect people away from more severe bodily harm and towards property damage.

4.2.2 *Institutions and Governance*

The key explanatory variables of our study are the institutional variables. According to previous studies, institutions are “the rules of the game in a society or, more formally, are the humanly devised constraints that shape human interaction” (North, 1990; Acemoglu and Robinson, 2010). In addition, we deem that institutions include governance and we use a set of institutional variables to represent the quality of governance. The World Bank defines governance as “the traditions and institutions by which authority in a country is exercised” (Kaufmann et al., 2010). In this spirit, we include the following indicators compiled by the World Bank: the *Government Effectiveness* and *Regulatory Quality* capture the capacity of the government to effectively formulate and implement sound policies; the *Rule of Law* and *Control of Corruption* represent the respect of citizens and the state for the institutions that govern economic and social interactions among them; the *Voice and Accountability* and *Regime Durability* indicates the process by which governments are selected, monitored, and replaced.

In addition to these six indicators, we include two other indicators that are related, but not equivalent, to good governance. The first one is the *Polity* score from the Center for Systemic Peace frequently used by scholars. Higher score means that a country is more democratic while lower score means the system is close to autocracy. We emphasize in this paper that we treat the polity score as an indicator of a country’s political status-quo or a de jure institution. This is the key

difference between this score and variables of governance, or the de facto institutions, that are based on surveys of citizens' feelings and opinions. Our statement that de facto institutions matter more than de jure institutions is stemmed from distinguishing these two concepts. Another one is the *Fractionalization Index* from the World Bank database of Political Institutions (2015) defined as "the probability that two deputies picked at random from the legislature will be of different parties?" (Keefer, 2012). Similarly, this index is more closely related to the de jure institution rather than to governance quality.

4.2.3 Descriptive Figures and Statistics

Table 4.1 reports the summary statistics for our main variables. The sample covers 159 countries. The time horizon for the economic and disaster variables is from 1979 to 2010, while the institutional variables are available since 1996.³ The statistics show that countries worldwide are quite different in the respect of their economic and institutional conditions: all variables have high standard deviations. For example, the average value of the per capital GDP is around \$8230, but the value at the 90th quantile is almost 37 times the value at the 10th quantile, showing the severe lack of balance in economic development. The disaster consequences share the same statistical property. The average mortality is greatly distorted by rare events, as it is bigger than the value at the 90th quantile. Probing the data, we find the largest death toll was caused by droughts and the resultant famine in Ethiopia during 1983 and 1984 that killed more than 560,000 people. In contrast to mortality, the largest economic losses usually happen in developed nations. For example, the biggest-ever economic damage was caused by the Hurricane Katrina in the U.S. in 2005, costing around \$146 billion. The following largest damages are related to the 1995 Kobe earthquake in Japan, the 1994 drought in China, and the 1998 country-wide floods in China.

To further understand the relationship among the three physical damage measures, we plot them in Figure 4.3. The immediate impression is that African countries usually suffer from massive mortality, whereas North America is mainly bothered by economic losses. This pattern testifies to the trade-off relationship among different damage measures. At the same time, it also brings a problem to our following estimation: once we regress the damage measures using three separate equations, we will obtain three different sets of efficiencies, making our conclusions inconsistent. Fortunately, with the output distance frontier model, we

³Merging datasets gives us the advantage of exploring the relationship between institutions and disaster relief but also leads to the reduction of observations. When there is a missing value in any one of the variables for an observation, we have to drop that observation.

Table 4.1: Key Statistics

This table summarizes descriptive statistics for the variables used in my baseline analyses. The sample includes three measures of disaster damage, i.e. the number of people killed, economic damage, and the number of people affected. The institutional variables are from the World Bank database, the natural pre-conditions, i.e. mean temperature and precipitation, are collected by the GeoMet dataset, and the economic pre-conditions are from the Penn World Table database. The sample covers 159 countries. The time horizon is 1979 to 2010.

	Average	Standard Deviation	10 th Percentile	90 th Percentile	Observations
<i>Pre-conditions</i>					
GDP per capita (\$)	8230.525	10339.33	672.728	24999.94	5482
Population (in millions)	147.041	303.578	3.717	288.471	5491
Capital stock (2011 U.S. \$ trillions)	3.468	8.091	0.019	8.621	5491
Country area (km ² millions)	2.014	3.423	0.032	9.148	5491
Mean temperature	19.981	9.337	5.218	28.179	5404
Mean precipitation (in millimeter)	3.975	3.017	0.705	8.360	5491
<i>Institutions</i>					
Government effectiveness	0.003	0.896	-0.954	1.603	3420
Control corruption	-0.129	0.925	-1.055	1.417	3420
Regime durability	22.987	25.526	2	49.000	4808
Voice and accountability	-0.063	0.913	-1.324	1.276	3420
Polity score	0.686	0.326	0.15	1	5360
Regulatory quality	0.012	0.869	-1.056	1.417	3420
Rule of law	-0.132	0.926	-1.138	1.478	3420
Fractionalization Index	0.502	0.302	0	0.827	4544
<i>Disaster consequences</i>					
Number of people killed	620.891	9350.246	2.071	200.577	3811
Number of people affected	1536.997	12264.560	0.205	1015.611	4472
Economic damage (\$ millions)	1109.574	5530.144	2.426	2059.921	2241

can incorporate these measures into one equation to get a single set of efficiencies. More interestingly, in this setting we can also quantify the trade-offs. As detailed in the Results section, we show that a rise in efficiency may mean a drop in mortality yet an increase in property damage. The next section discusses our method.

4.3 Empirical Methodology

To estimate countries' efficiencies for disaster mitigation, we employ the stochastic frontier analysis that provides us with a benchmark for comparing countries. Specifically, in our study, we construct a "frontier" consisting of the disaster costs that countries are expected to suffer given their preconditions and disaster intensity such as population, capital stock, and the average temperature of the month when a disaster happens. For instance, in Figure 4.4, countries A, B, and C have their own ideal costs, A^* , B^* , and C^* , respectively on the frontier curve. However, due to inefficiency, the actual costs are always bigger than the ideal costs. The efficiency for each country is thus expressed as the ratio of the minimum cost to

Figure 4.3: Continents Feature Different Types of Damages. This bar chart plots the average values of each of the three scaled damage measures, i.e. people killed per thousand population, people affected per million population, and economic damage per dollar GDP by continents. We scale killed and affected people differently to improve the readability of the figure. The data source is the EM-DAT dataset with the time horizon from 1979 to 2010. The figure indicates that for African countries, the biggest consequence of disaster is the massive mortality whereas Europe and North America, compared with other continents, have relatively high per GDP economic losses.

the realized cost. When the ratio is one, it means the country suffers least and is most efficient. The output distance frontier model is nested in the stochastic frontier approach; it is designed for a multiple-output case as in our context.

4.3.1 Deriving the Baseline Empirical Model

To elaborate our output distance model, Figure 4.4 continues to serve as a good single-output example on hand. Let y denote the actual output, which is the realized cost in our study, given the preconditions (inputs) x , and let y^* represent the minimum disaster impact determined by a disaster-relief function $f(x)$. Now, suppose we want to move y a bit closer to the frontier so as to increase the efficiency, then we need to divide y by a quantity greater than one. For the time being, name this quantity as the distance ratio, and then the largest value of this distance ratio is y/y^* because y divided by y/y^* is y^* . Put it plainly, the output distance is in fact the maximum distance ratio that can shift the actual output towards the frontier, but at the same time still keeps the actual output within the boundary of the frontier.⁴ More generally, we define the distance function as:

$$O(y, x) = \arg \max_{\theta} \left\{ \frac{y}{\theta} \geq d(x) \right\}, \quad (4.1)$$

where $d(x)$ is the minimum possible disaster cost given the economic conditions and event intensity x . Analogously, in the multiple output case, the feasible set for all the outputs should be a set of values, say $\mathcal{D}(x)$. Therefore, the output distance function is defined as:

$$O(y, x) = \arg \max_{\theta} \left\{ \frac{y}{\theta} \in \mathcal{D}(x) \right\}, \quad (4.2)$$

where $y = (y_1, \dots, y_M)$ is a vector of outputs. To estimate the model, however, the inputs and outputs should be separated. We achieve this by assuming that the distance function is homogeneous of degree one in y .⁵ As a result, by dividing

⁴Suppose the distance ratio is not y/y^* but a bit larger, say, $y/(y^* - \epsilon)$, where ϵ is positive. This means we move y to $y^* - \epsilon$ which is outside the frontier. Therefore, the maximum distance ratio is y/y^* .

⁵This is a simplistic assumption because it means that when y doubles, the distance becomes $2y/y^*$, given that the minimum unavoidable damage y^* does not change. This, however, is restrictive because if the actual cost is high, the ideal cost also tends to be high, making the distance ratio a bit lower than $2y/y^*$. However, if we fully relax this assumption and say that the distance function is homogeneous of degree k in y , the results does not change because k is a constant and is absorbed into the coefficients in the following translog equation. Finally, the relative ranks of the estimated efficiencies do not change.

the distance function by the first output y_1 , we obtain:⁶

$$\frac{O(y, x)}{y_1} = h\left(x, \frac{y_2}{y_1}, \dots, \frac{y_M}{y_1}\right), \quad (4.3)$$

where $h(\cdot)$ is a parametric regression function. Taking the logarithms on both sides of the equation and assigning a normal disturbance term to the right-hand side, we have:⁷

$$\ln O(y, x) - \ln y_1 = \ln h\left(x, \frac{y_2}{y_1}, \dots, \frac{y_M}{y_1}\right) - v_{it}. \quad (4.4)$$

Finally, denoting $\ln O(y, x) = u \geq 0$ and using a translog form of the regression equation, our generic estimation model is as follows:

$$\begin{aligned} -\ln y_{1it} = & \alpha_i + \sum_{k=1}^K \alpha_k \ln x_{kit} + \sum_{m=2}^M \beta_m \ln \hat{y}_{mit} + \frac{1}{2} \sum_{k=1}^K \sum_{k'=1}^K \alpha_{kk'} \ln x_{kit} \ln x_{k'it} \\ & + \frac{1}{2} \sum_{m=2}^M \sum_{m'=2}^M \beta_{mm'} \ln \hat{y}_{mit} \ln \hat{y}_{m'it} + \frac{1}{2} \sum_{k=1}^K \sum_{m=2}^M \alpha_{km} \ln x_{kit} \ln \hat{y}_{mit} - u_{it} - v_{it}, \end{aligned} \quad (4.5)$$

where $\hat{y}_{mit} = y_{mit}/y_{1it}$ is the modified m^{th} damage of country i at time t , α_i 's are country fixed effects, and v_{it} is the error term. The time unit is in month.

4.3.2 Incorporating Institutional Variables

In Equation 4.5, the inefficiency component is $u_{it} \geq 0$. It is assumed to follow a truncated normal distribution, $|N(\mu_{it}, \sigma_{it}^2)|$, with the truncation point at μ . Apparently, the higher the μ is, the less efficient is a country on average. More important, in our model, this truncation point is determined by the institutional variable z :

$$\mu_{it} = \delta + \eta z_{it}, \quad (4.6)$$

where, as will be detailed later, z_{it} takes the value of either one of the following institutional variables: government effectiveness, control of corruption, regime durability, voice and accountability, polity score, regulatory quality, rule of law, and political party diversity. Our coefficient of interest is η , which we expect to be negative.

⁶In our estimation, we choose the economic damage as our dependent variable y_1 and include $\ln(\text{number of people killed/damage})$ and $\ln(\text{number of people affected/damage})$ as explanatory variables. However, the results does not change if we choose the other two measures as our dependent variables.

⁷Since the disturbance v_{it} is normally distributed, whether we use the minus sign or plus sign has no effect on the model. However, as we will estimate a cost-type stochastic frontier model, we subtract v_{it} to be consistent with the standard specification.

Figure 4.4: How to Measure Efficiency in a Cost Frontier Model. This figure illustrates the theoretical rationale of our stochastic frontier model used for estimating disaster relief efficiencies. Here, the curve represents the cost, i.e. disaster damage, frontier. Suppose country A currently has an input level at X_A , then according to the model, the minimum damage it can expect after a natural disaster is A^* on the frontier. If the actual damage, however, is A , then the efficiency of country A in reducing disaster costs is $\frac{X_A A^*}{X_A A}$. The bigger the value of A , the lower the efficiency. It is easy to realize that regarding efficiency, country C is higher than B which is higher than A.

To account for possible second-moment effects of institutional variables, we further allow the variance of inefficiency to be determined by institutions:

$$\sigma_{it}^2 = \exp(\lambda + \psi z_{it}). \quad (4.7)$$

Again, given that this study emphasizes on the effects of institutions, Equation 4.6 describes the most important relationship of our empirical analyses. Together with Equation 4.5, they will tell us how the hardware, e.g. population, capital stock, and software, e.g. anti-corruption efforts, contribute to the mitigation of disaster damage and the (in)efficiency of alleviating disasters.

Finally, as $u_{it} \geq 0$ stands for a country's inefficiency, for interpretation convenience, we transform it to efficiency:

$$e_{it} = \exp(-u_{it}), \quad (4.8)$$

where $e_{it} \in (0, 1]$ represents the country- and year-specific efficiency in disaster mitigation. The parameters in Equations 4.5 and 4.6 are estimated by the maximum likelihood method. In the next section, we present our main results.

4.4 Results

In this section, we present our key results on the efficiencies of countries in disaster mitigation and the role played by good governance in promoting the efficiency. I find countries with good governance qualities perform better in saving people's lives during disastrous times, but the indicator for democracy level has an ambiguous effect. We also discuss causality issues and test other specifications as robustness checks.

4.4.1 How Do Countries Differ in Efficiencies?

We start by presenting the ranks of disaster-relief efficiencies. As shown in Figure 4.5, the first three plots display highly uniform ranks. For example, during 1996 to 2010, New Zealand on average has performed best in disaster mitigation. It is followed by other developed nations such as Canada, Japan, and the United States. Developing countries usually have a middle rank. For instance, in the first plot, China, India, and Brazil rank at the 27th, 31st, and 32nd positions respectively.⁸ The figure seems hint at that rich countries, i.e. countries in general

⁸Our specific estimation procedure is as follows: for each estimation, we include one institutional variable as the z variable in Equation 4.6. The estimation yields country- and year-specific efficiencies. We then average efficiencies across years to obtain the final scores.

Figure 4.5: Disaster Relief Efficiency Rank. This figure shows the rank of countries by their disaster relief efficiencies. The efficiency values in each plot are estimated by the output distance model using government effectiveness, control of corruption, regime durability, and the polity score as the institutional variable respectively.

with better institutions, tend to perform better. However, these scores are only cross-sectional. In the next subsection, we formally show our panel data results.

4.4.2 Can Institutions Affect Efficiencies?

Table 4.2 reports results from the stochastic frontier regressions of institutional variables on inefficiencies, i.e. the estimated η 's of Equation 4.6.⁹ The results indicate a significantly negative relationship between disaster-relief inefficiency and institutions, especially those reflect governance quality. These governance variables, such as government effectiveness, control of corruption, regime durability, voice and accountability, and regulatory quality, reduce the inefficiency, i.e. promote the efficiency. Meanwhile, better institutions also mitigate the volatility of the (in)efficiency.¹⁰ We find, however, an insignificantly positive coefficient on

⁹Since η_{it} and z_{it} , together determines the mean value of the inefficiency, a positive η_{it} indicates that the institutional variable z_{it} is positively related to inefficiency. This relationship, however, is still not economically intuitive. We will show the economic significance in the next paragraph using figures.

¹⁰Intuitively, better institutions lead to stable performance in disaster relief. Further, countries with better institutions are developed nations that have undergone less political and economic reforms. The stable economic and political environment can contribute to the low volatility of efficiency.

the rule of law and a significantly positive relationship between polity score and inefficiency.¹¹ In the full table with all control variables shown in the Appendix, we also find significantly positive effects of earthquake magnitude and storm wind speed on the economic damage.

The economic effect of institutions on efficiency is significant. Figure 4.6 depicts the relationship between the estimated efficiencies and institutional variables. For the government effectiveness, we notice that if the indicator score increases by 1, then the efficiency will increase about 0.16 (or 16 percent as efficiency score is between 0 and 1). Similarly for the control of corruption, the efficiency will rise by about 40% when the control of corruption score increases by 1.¹² Further, if the political system lasts 10 years longer, the efficiency will increase by roughly 6%. In view that we have controlled for all country fixed effects, this finding reveals that a stable political system helps countries and citizens to endure adverse events. In addition, we observe the slopes of the curves become steeper as the scores increase. This means that the effects of governance quality are more pronounced for countries that already have good quality.¹³

¹¹This finding is at the first sight surprising. By checking the correlations between the polity score and other institutional variables, we find they are positive, but to a very small extent. In the later robustness check, using an alternative model, we find that the polity score contribute positively to efficiency. At this stage, we conclude that the de jure institution is at least not a strong indicator for disaster-relief efficiency.

¹²As a reminder to the reader of the summary statistics, the control of corruption score has a standard deviation of 0.92, with the minimum and maximum values to be -1.98 and 2.53 respectively.

¹³From a technical point of view, this fast increasing curve is as expected by construction. Looking at Equations 4.6 and 4.8, we notice the effect of the institutional variable on efficiency is $\frac{de_{it}}{dz_{it}} = \frac{de_{it}}{du_{it}} \frac{du_{it}}{dz_{it}} = -\exp(-u_{it})\eta$. As inefficiency decreases from large values towards 0, the exponential term increases faster and faster. In short, the fast increasing curve is mainly caused by transforming from inefficiency to efficiency using $e_{it} = \exp(-u_{it})$.

Table 4.2: Effects of Institutional Variables on Inefficiency

This table reports the effects of countries' institutional variables on their disaster-relief inefficiency. We include worldwide disasters taking place between 1996M1 and 2010M12 and control for countries' natural and economic pre-conditions. The institutional variables include measures of government effectiveness, control of corruption, regime durability, voice and accountability, level of democracy (the polity score), rule of law, and the political party heterogeneity (the fractionalization index), as reported in the World Bank dataset. Natural pre-conditions, e.g. mean temperature, mean precipitation, are from the EM-DAT database, and economic control variables, e.g. population, capital stock, GDP per capita, country area, are from the Penn World Table. Coefficients of the control variables are reported in Table 4.5 in the Appendix. As we have three measures of disaster damage (i.e. number of people killed, monetary damage, and number of people affected), we choose the output distance frontier method, a modified stochastic frontier approach that helps us to estimate (in)efficiency using a single equation. We impose a rather loose assumption that inefficiency has a truncated-normal distribution while letting the model to determine the location of the truncation point, which is a function of the institutional variable. For each institutional variable, the effect on the mean of the inefficiency is reported at the first two rows whereas the effect on the variance of the inefficiency is reported at the second two rows. We also report the average disaster relief efficiency across years and countries. The standard errors are reported in parentheses. All the regressions control for the country fixed effects.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Government effectiveness	-1.460 (0.534)							
Government effectiveness	-0.617 (0.402)							
Control corruption		-1.380 (0.411)						
Control corruption		-0.821 (0.486)						
Regime durability			-0.036 (0.012)					
Regime durability			-0.003 (0.007)					
Voice and accountability				-1.436 (0.547)				
Voice and accountability				-0.553 (0.248)				

Continued	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Polity score					4.544 (2.466)			
Polity score					-4.701 (1.654)			
Regulatory quality						-1.377 (0.553)		
Regulatory quality						-1.018 (0.565)		
Rule of law							0.049 (0.560)	
Rule of law							-0.767 (0.528)	
Fractionalization Index								0.382 (0.534)
Fractionalization Index								-16.916 (30.635)
Average efficiency	0.297	0.299	0.125	0.287	0.445	0.368	0.001	0.378
Observations	617	617	881	617	1007	593	593	788
Log likelihood	-1095.040	-1093.029	-1587.564	-1091.002	-1801.538	-1030.343	-1018.587	-1401.373
Wald χ^2	1213.05	1214.86	1527.43	1238.26	1888.09	1362.71	1403.38	1751.71

Figure 4.6: Disaster Relief Efficiency and Institutional Variables. This figure shows the scatter plots of the relationship between each institutional variable and the disaster relief efficiency estimated by the stochastic output distance model. The plots show significant positive relationship between disaster relief efficiency and governance measures, e.g. government effectiveness, control of corruption, regime durability, voice and accountability.

4.4.3 Can Countries Better Handle Disasters by Reforming Institutions?

In this subsection, we look at the time dimension of efficiency and institutions. To explore how efficiencies for different countries have evolved over time, we plot in Figure 4.7 the estimated efficiencies (based on the government effectiveness measure) and two governance quality indicators, i.e. government effectiveness and control of corruption (both drawn against the right y-axis), for six countries during 1996 to 2010. To improve the readability, the indicator values are normalized to be within 0 and 1.¹⁴

A first glance at the figure informs us the efficiencies are very volatile while the institutions are persistent. The high volatility of the efficiencies is because disaster damages and economic conditions vary heavily over time, leading to big fluctuations in the effectiveness of alleviating disasters.¹⁵ The persistency in institutions corroborate the theory of Acemoglu et al. (2011), which states that the coalition between the rich and the bureaucrats renders the country to be persistently inefficient.

However, trends do exist especially when we ignore a few outliers. For the United States, though efficiencies are on average very high, we can still notice a decreasing trend in efficiency since the beginning of the new century. And importantly, this trend is in sync with the governance quality: both the government effectiveness and control of corruption scores have been decreasing. In contrast, China, Japan, and India witness a gradual improvement of their governance quality. Interestingly, during the same period, their disaster mitigation efficiencies are increasing.¹⁶ Viewing that China and India have been undergoing active political and economic reforms, it is easy to infer that these reforms have improved governance quality, therefore promoting their efficiency in mitigating natural hazards. As for France and Brazil, the relationship is weak and their efficiencies and institutions have on average stayed constant over the past years.

¹⁴For instance, for the government effectiveness score z_{it} , the normalized value is $\bar{z}_{it} = (z_{it} - \min\{z\})/(\max\{z\} - \min\{z\})$.

¹⁵The high volatility is just one aspect of efficiencies because it is inferred based on the time series of a single country. If we compare efficiencies of different countries, we find that countries with high (low) efficiencies remain at a high (low) rank. In this aspect, efficiencies are persistent.

¹⁶The positive relationship between efficiency and institutions are more pronounced for Japan and India. For China, the most synchronized relationship appears in the late 1990s and early 2000s when efficiencies dropped as the control of corruption decreased.

Figure 4.7: Countries Can Improve Efficiency by Reforming Institutions. This figure plots the time series values of disaster relief efficiencies for the United States, China, Japan, India, France, and Brazil estimated using the output distance model with government effectiveness as the institutional variable. The disaster events are represented by the circles. Values of government effectiveness and control of corruption are normalized between 0 and 1 and are plotted against the right y-axis. The plots show that the disaster relief efficiency is positively correlated with the quality of governance. For the United States, the estimated efficiencies and measures of governance jointly go down after 2000. Meanwhile, China and India experience increases in their efficiencies and well as governance quality in recent years. The time series plots for the institutional variables further confirm that institutions are very persistent.

4.4.4 Back from Efficiencies to Real Damages

So far, we have achieved our main goal of elaborating how good governance can help countries in relieving disasters. In particular, to compare countries on a uniform benchmark, we have introduced the estimation model, producing the country- and year-specific efficiencies. But what does efficiency mean for people and their properties? In this subsection, we complete our reasoning circle by answering this question.

Figure 4.8 uses two scatter plots to show the relationships between efficiency and mortality, and efficiency and economic damages respectively.¹⁷ The figure shows obviously that mortality is negatively related to efficiency whereas damage has a clear positive relationship with efficiency. Such pattern is more pronounced for countries in Asia, North America, and Oceania and less pronounced for African countries. Our take-away lesson from these findings is that, there does exist a trade-off between saving people's lives and reducing material damages. As countries improve their governance quality and disaster-relief capacity, they emphasize preventing human losses and will suffer more material damages as a consequence. This also has to do with investments in costly infrastructures to prevent loss of lives. Thus, by giving up materials, more lives are saved.

Figure 4.8: Disaster Relief Efficiency and Cost Variables. This figure shows the scatter plots of the relationship between efficiency and mortality and damage. The plots show a significantly negative relationship between disaster relief efficiency and number of people killed (left panel, in log) and a significantly positive relationship between efficiency and material damage (right panel, in log).

¹⁷The efficiencies are estimated using government effectiveness as the institutional variable. The results based on other de facto institutional measures are similar.

4.4.5 Robustness Discussions

Half Normal Inefficiency

One advantage of our baseline model is assuming the inefficiency term follows a truncated-normal distribution. In this way, we can let the institutional variable itself determine the truncation point and can estimate the coefficients simply in one step. Now we try another frequently used setting by assuming that the inefficiency term has a standard half normal distribution. In such a way a country's mean value of the efficiency is constant and is not determined by institutions. We then find the relationship between efficiencies and the institutional variables using simple OLS method. Table 4.4 shows a clear negative relationship for all the institutional variables. Besides, Figure 4.9 plots the distributions of the estimated country- and time-specific efficiencies under the truncated-normal and half-normal settings. The half-normal assumption clearly yields a more concentrated and nicely-shaped distribution. The truncated-normal model, nevertheless, generates distributions with significantly lower efficiency values and the spreads are high. The high spread represents the fact that in reality countries differ heavily in their disaster reliefs. Such a comparison testifies to the significant role of institutional variables in determining disaster-relief efficiencies.

Causality Inferences

We emphasize that, in this study, we make no statement that better institutions cause higher efficiency. Instead, we have proved that better governance shield people from natural disasters by promoting countries' disaster-relief efficiency. Besides, better governance also implies protecting lives at the cost of material damage.

Even though our paper shows a battery of relationships among institutional quality, disaster-relief efficiency, mortality, and damage, we do not formally test the causal relationship between institutions and efficiency. First, in many contexts, including this research, natural disasters are not exogenous shocks. Not to mention ancient times, even in modern societies, we have reasons to believe that countries who have frequently been suffering from natural hazards decided to improve their institutions. As a result, information becomes more transparent, corruption is restrained, and therefore efficiencies increase.¹⁸ Second, efficiency is an estimated

¹⁸Ancient Chinese elites believe natural disasters to be a sign of the heaven's discontentment with the rulers. The famous Chinese history classics, *Zizhi Tongjian* (literally "Comprehensive Mirror in Aid of Governance") that covers the period from 403 B.C. to 959 A.D. contains numerous examples of rulers' adjusting their policies after natural catastrophes.

Figure 4.9: Disaster Relief Efficiency Distribution. We plot histograms for disaster relief efficiency. In the top panel, we estimate a stochastic frontier model where the inefficiency term u follows a truncated normal distribution. Crucially, we let the institutional variable to determine both the truncation point and the variance. Each set of values of efficiency is based on an estimation with one of the four institutional variables, i.e. government effectiveness, control corruption, polity score, and regime durability, affecting the efficiency. In the bottom panel, we impose a stricter assumption that the inefficiency follows a half-normal distribution and we let the institution affect only the variance term.

outcome rather than a real variable, so the pursuit of a causal interpretation is not well-based in this context. In spite of that, our comprehensive data surely allows us to undertake causal studies in future research.

4.5 Conclusion

The political economy of development has long been trying to understand how to improve the efficiency of institutions. We contribute to this discussion by looking at the disaster mitigation behavior and by using a comprehensive dataset that provides us with disaster intensity and different measures of damage. We provide a model that helps to evaluate and rank countries' disaster-relief efficiency and we explore institutional variables leading to higher efficiency.

Countries differ largely in their disaster-relief efficiencies, with richer countries performing better than poorer countries. We find a positive relationship between efficiency and institutions. In particular, indicators of good governance have significantly positive effects on efficiencies, whereas variables reflecting the *de jure* institutions are not informative. Importantly, with the output distance model, our study captures the trade-off relationship between saving people and reducing material damage during disaster mitigation. Specifically, a 0.625 increase in the government effectiveness score on average leads to a 10% increase in efficiency, which implies a 11.46% decrease in the number of people killed but a 50.69% increase in material damage.¹⁹ Finally, we show that countries that have been improving their governance qualities in the past years experience increases in their disaster-mitigation efficiencies.

Looking into the future, we deem using microlevel data to identify the relationship between municipal level institutions and disaster-relief performance as a possible research avenue.

¹⁹Notice that in the Results section we have shown that a 1 score increase in the government effectiveness leads to a 16% increase in efficiency. Therefore, a 10% increase in efficiency is associated with a 0.625 increase in the score.

Appendix

Table 4.3: Countries' Efficiency Ranks Using Government Effectiveness as the Institutional Variable

This table presents the ranks of countries by their disaster-relief efficiencies. The efficiencies are based on the output distance model using the government effectiveness as the institutional variable. The corresponding graph is the top left plot in Figure 4.5.

Rank	Country	Rank	Country
1	New Zealand	29	Colombia
2	Austria	30	Philippines
3	Switzerland	31	India
4	Canada	32	Brazil
5	United Kingdom	33	Morocco
6	Germany	34	Ghana
7	Australia	35	Saudi Arabia
8	Spain	36	Indonesia
9	United States	37	Peru
10	Belgium	38	Viet Nam
11	France	39	Kenya
12	Japan	40	Venezuela
13	Chile	41	Pakistan
14	Israel	42	Malawi
15	Malaysia	43	Mozambique
16	Taiwan	44	Kazakhstan
17	Slovenia	45	Russian Federation
18	Hungary	46	Bolivia
19	Republic of Korea	47	Madagascar
20	Italy	48	Kyrgyzstan
21	South Africa	49	Uganda
22	Poland	50	Burkina Faso
23	Botswana	51	Ethiopia
24	Mauritius	52	Nigeria
25	Mexico	53	Zimbabwe
26	Turkey	54	Chad
27	China	55	Angola
28	Argentina	56	D.R. of the Congo

Table 4.4: Effects of Institutional Variables on Disaster Relief Efficiency Assuming Half-Normal Distribution

This table reports the effects of countries' institutional variables on their disaster relief inefficiency using the output distance model. Unlike the main analysis as reported by Table ??, here we impose the assumption that the inefficiency follows a half-normal distribution, which is a fold at the mean of an ordinary normal distribution with mean zero. The effects of institutions are further obtained by running a linear regression of the estimated inefficiency on each institutional variable. The variance of inefficiency is still a function of the institutional variable. For each institutional variable, the effect on the mean of the inefficiency is reported at the first two rows whereas the effect on the variance of the inefficiency is reported at the second two rows. We also report the average disaster relief efficiency across years and countries. The standard errors are reported in parentheses. All linear regressions control for the year fixed effects.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Government effectiveness	-0.280 (0.011)							
Government effectiveness	-1.166 (0.457)							
Control corruption		-0.262 (0.010)						
Control corruption		-1.148 (0.463)						
Regime durability			-0.003 (0.000)					
Regime durability			-0.038 (0.065)					
Voice and accountability				-0.311 (0.012)				
Voice and accountability				-1.068 (0.345)				

Continued	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Polity score					-0.195 (0.003)			
Polity score					-1.558 (2.541)			
Regulatory quality						-0.418 (0.019)		
Regulatory quality						-1.578 (0.460)		
Rule of law							-0.444 (0.020)	
Rule of law							-1.576 (0.425)	
Fractionalization Index								-0.221 (0.004)
Fractionalization Index								-1.793 (2.510)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Average efficiency	0.574	0.575	0.780	0.583	0.784	0.543	0.532	0.783
Observations	617	617	881	617	1007	593	593	838
Log likelihood	-1098.276	-1097.734	-1590.867	-1095.468	-1805.726	-1033.523	-1030.948	-1486.631
Wald χ^2	1242.88	1225.12	1543.56	1351.7	2101.89	1436.4	1381.94	1825.77

Table 4.5: Effects of Institutional Variables on Disaster Relief Efficiency Estimated by Output Distance Frontier Method (Full Table)

This table reports the effects of countries' institutional variables on their disaster relief efficiency using the output distance frontier method. We include worldwide disasters taking place between 1996M1 and 2010M12 and control for countries' natural and economic pre-conditions. The institutional variables include measures of government effectiveness, control of corruption, regime durability, voice accountability, level of democracy (the polity score), rule of law, and the degree of ethnic, linguistic and religious heterogeneity (the fractionalization index), as reported in the World Bank dataset. Natural pre-conditions, e.g. mean temperature, mean precipitation, are from the EM-DAT database, and economic control variables, e.g. population, capital stock, GDP per capita, country area, are from the Penn World Table. As we have three measures of disaster damage (i.e. number of people killed, monetary damage, and number of people affected), we choose the output distance frontier method, a modified stochastic frontier approach that helps us to estimate efficiency using a single equation. We impose a rather loose assumption that inefficiency has a truncated-normal distribution while letting the model to determine the location of the truncation point, which is a function of the institutional variable. The depend variable is $-\ln(\text{damage})$; as a result, when interpreting coefficients, a minus sign should be taken into account. For each institutional variable, the effect on the mean of the efficiency is reported at the first two rows whereas the effect on the variance of the efficiency is reported at the second two rows. We also report the average disaster relief efficiency across years and countries. The standard errors are reported in parentheses. All the regressions control for the country fixed effects.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Frontier								
lnpopsqkm	-37.777 (22.781)	-42.563 (22.820)	11.238 (11.200)	-46.859 (22.013)	5.043 (10.829)	-49.222 (27.959)	-24.903 (28.097)	-7.964 (16.307)
lncksqkm	37.626 (20.755)	43.934 (20.707)	-15.514 (11.134)	48.590 (20.253)	-6.989 (10.654)	44.355 (24.536)	22.997 (25.024)	11.030 (15.471)
lcgdp	-47.506 (24.541)	-56.600 (24.711)	16.138 (12.609)	-59.338 (24.343)	9.950 (12.150)	-53.511 (27.341)	-25.570 (27.241)	-10.003 (17.653)
lnaffected	0.923 (1.694)	0.884 (1.681)	1.902 (0.992)	0.780 (1.597)	2.097 (0.938)	-0.795 (1.551)	-1.115 (1.545)	0.840 (1.144)
lnkilled	-2.856 (2.340)	-2.257 (2.329)	-1.111 (1.171)	-1.794 (2.230)	-1.787 (1.127)	-2.355 (2.070)	-2.608 (2.051)	-1.017 (1.374)
lnpopsqkm2	2.233 (2.653)	2.268 (2.659)	-0.656 (1.093)	2.972 (2.575)	-0.230 (1.052)	3.511 (3.036)	2.437 (3.057)	-0.127 (1.602)
lncksqkm2	2.739 (1.560)	3.038 (1.547)	-1.063 (0.847)	3.481 (1.502)	-0.322 (0.806)	3.112 (1.946)	1.589 (1.999)	1.223 (1.204)
lcgdp2	4.152 (2.093)	4.896 (2.105)	-1.241 (1.056)	5.053 (2.079)	-0.769 (1.023)	4.654 (2.309)	2.289 (2.291)	0.687 (1.496)
lnaffected2	-0.010 (0.013)	-0.011 (0.013)	-0.002 (0.011)	-0.007 (0.013)	0.001 (0.011)	-0.002 (0.013)	0.004 (0.012)	0.005 (0.012)
lnkilled2	-0.021 (0.025)	-0.022 (0.024)	-0.004 (0.018)	-0.025 (0.025)	-0.015 (0.017)	-0.025 (0.026)	-0.018 (0.025)	-0.020 (0.022)
lnpopsqkm	-2.369 (1.506)	-2.795 (1.498)	0.743 (0.819)	-3.254 (1.439)	0.117 (0.786)	-3.053 (1.967)	-1.544 (2.026)	-1.193 (1.168)
lncksqkm	3.567 (1.729)	4.110 (1.737)	-1.012 (0.954)	4.415 (1.683)	-0.419 (0.914)	3.879 (2.060)	1.736 (2.077)	1.289 (1.323)

CHAPTER 4

Continued

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
lnpopsqkmlnaaffected	-0.103 (0.127)	-0.102 (0.126)	-0.200 (0.073)	-0.091 (0.119)	-0.222 (0.069)	0.027 (0.116)	0.044 (0.115)	-0.119 (0.083)
lnpopsqkmlnkilled	0.213 (0.175)	0.167 (0.174)	0.120 (0.089)	0.132 (0.166)	0.159 (0.086)	0.146 (0.156)	0.172 (0.155)	0.090 (0.104)
lncksqkmlcgdp	-3.500 (1.762)	-4.005 (1.757)	1.317 (0.946)	-4.300 (1.726)	0.601 (0.906)	-3.923 (2.021)	-2.067 (2.046)	-0.920 (1.306)
lncksqkmlnaaffected	0.054 (0.128)	0.052 (0.128)	0.150 (0.076)	0.040 (0.121)	0.176 (0.072)	-0.031 (0.116)	-0.053 (0.115)	0.117 (0.086)
lncksqkmlnkilled	-0.158 (0.175)	-0.114 (0.174)	-0.069 (0.091)	-0.074 (0.166)	-0.114 (0.087)	-0.120 (0.154)	-0.152 (0.152)	-0.059 (0.105)
lcgdpnaaffected	-0.042 (0.137)	-0.037 (0.136)	-0.118 (0.082)	-0.032 (0.130)	-0.130 (0.077)	0.089 (0.126)	0.114 (0.125)	-0.037 (0.095)
lcgdpnkilled	0.282 (0.190)	0.234 (0.190)	0.132 (0.098)	0.195 (0.182)	0.192 (0.094)	0.250 (0.169)	0.275 (0.167)	0.130 (0.115)
lnaffectedlnkilled	0.056 (0.014)	0.056 (0.014)	0.045 (0.011)	0.054 (0.014)	0.047 (0.011)	0.058 (0.015)	0.052 (0.014)	0.046 (0.013)
magnitude during the disaster	-0.133 (0.046)	-0.133 (0.045)	-0.061 (0.035)	-0.142 (0.046)	-0.097 (0.034)	-0.173 (0.047)	-0.170 (0.048)	-0.142 (0.038)
wind speed during the disaster	-0.007 (0.002)	-0.008 (0.002)	0.001 (0.002)	-0.009 (0.003)	-0.004 (0.002)	-0.009 (0.002)	-0.011 (0.002)	-0.005 (0.002)
precipitation during the disaster	-0.045 (0.045)	-0.068 (0.045)	0.037 (0.035)	-0.067 (0.044)	-0.004 (0.033)	-0.089 (0.046)	-0.110 (0.047)	-0.054 (0.039)
mean temperature	0.019 (0.011)	0.021 (0.011)	0.008 (0.011)	0.021 (0.011)	0.009 (0.009)	0.013 (0.010)	0.015 (0.010)	0.000 (0.010)
mean precipitation	-0.019 (0.048)	-0.008 (0.048)	-0.058 (0.039)	0.001 (0.047)	-0.033 (0.036)	-0.107 (0.057)	-0.098 (0.057)	-0.082 (0.049)
cumulative disaster count	-0.002 (0.005)	-0.004 (0.005)	0.011 (0.004)	-0.006 (0.005)	0.001 (0.003)	0.001 (0.005)	0.002 (0.005)	0.004 (0.004)
Efficiency								
Government effectiveness	-1.460 (0.534)							
Government effectiveness	-0.617 (0.402)							
Control corruption		-1.380 (0.411)						
Control corruption		-0.821 (0.486)						
Regime durability			-0.036 (0.012)					

Continued

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Regime durability			-0.003 (0.007)					
Voice and accountability				-1.436 (0.547)				
Voice and accountability				-0.553 (0.248)				
Polity score					4.544 (2.466)			
Polity score					-4.701 (1.654)			
Regulatory quality						-1.377 (0.553)		
Regulatory quality						-1.018 (0.565)		
Rule of law							0.049 (0.560)	
Rule of law							-0.767 (0.528)	
Fractionalization Index								0.382 (0.534)
Fractionalization Index								-16.916 (30.635)
Average efficiency	0.297	0.299	0.125	0.287	0.445	0.368	0.001	0.378
Observations	617	617	881	617	1007	593	593	788
Log likelihood	-1095.040	-1093.029	-1587.564	-1091.002	-1801.538	-1030.343	-1018.587	-1401.373
Wald χ^2	1213.05	1214.86	1527.43	1238.26	1888.09	1362.71	1403.38	1751.71

Conclusions

This dissertation has three major conclusions.

First, banks' risk attitudes and business models are affected by disaster experiences. Experiences are not only important to people, but also crucial to institutions (Berger and Udell, 2004). Financial institutions with disastrous experiences become more conservative and are not willing to undertake risky businesses, which is harmful to economic development. In addition, banks can become biased against poorer borrowers and reduce lending to them, thus worsening the inequality issue. Communities with stronger disaster experiences are dwelt with fewer rich people and have less deposit, weakening the momentum for future development. We therefore need to be aware of these downsides and try to stimulate banking and reduce inequalities if those disaster-prone regions are important for a country's long-term strategy.

Second, by strategically allocating assets, banks can serve the increased demand for funds from communities after natural disasters. Disasters damage firms' production capital, reduce banks' existing assets by triggering default yet increase the demand for loans due to less capital stock. I document the existence of the asset allocation behavior using a difference-in-difference analysis. Further, using a multiple-asset dynamic credit rationing model, I show how banks can allocate different types of loans and securities to satisfy public needs but also benefit banks' themselves.

Third, countries can improve their disaster mitigation by reforming institutions. Countries differ largely in their disaster-relief efficiencies, with richer countries performing better than poorer countries. There is a positive relationship between efficiency and institutional quality. Indicators of good governance have significantly positive effects on efficiencies. Importantly, the stochastic frontier model captures the trade-off between rescuing people and reducing material damage. I also document that emerging countries, such as China and India, experience increases in their disaster-mitigation efficiencies by improving their governance qualities in the last decades.

Looking into the future, I deem using microlevel data to identify the interactions among disasters, financial innovation, household finance, urban development, and political institutions as possible research topics.

Valorization

Natural disasters impose tremendous risks to people's lives. Throughout history, human beings have developed various methods to prevent natural hazards and to reduce the negative impact in the aftermath. In modern times, thanks to financial innovations, people can use insurance and can buy and sell insurance-equivalent financial instruments such as cat bonds to reduce losses. Notwithstanding these financial innovations, traditional bank credit supply and government assistance still play a vital role in disaster mitigation (Kunreuther and Linnerooth-Bayer, 2003; Linnerooth-Bayer and Hochrainer-Stigler, 2015; Beck et al., 2010). We need to know more about how financial institutions and government services can reduce the impact of disasters. This dissertation contributes to this goal by studying how banks react to natural hazards in long and short terms and the role of good governance in limiting disaster damage.

Chapter 2 has three contributions. First, this study is the first to choose the long-term view to examine disasters' impact on banks. On the one hand, we can understand whether the balance sheet structure can be explained by banks' disaster experiences. Banks that repeatedly experience disaster-related defaults tend to purposefully contract their real estate lending, imposing a negative impact on the economy. On the other hand, we can also explore the evolution of other non-financial sectors. Intense disaster experiences may lead to reallocation of economic activities from one county to another. I indeed find that, in the long run, residents reduce their savings and their real estate borrowing. The long-run analysis therefore captures a gradual demographic and economic evolution. Second, I show that strong disaster experiences lead banks to reduce their lending to low-income borrowers. This finding reveals the existence of disaster-driven lending bias, and therefore, government intervention is crucial in protecting economically disadvantaged groups. Third, by showing that banks have longer memory for past events than individuals do, the chapter implies that institutions are slow in adapting themselves to new situations, making it necessary for policy makers to intervene.

The contributions of Chapter 3 consist of an empirical one and a theoretical one. On the empirical side, I show that credit allocation after natural disasters obeys the law of demand and supply. More specifically, banks issue more loans because of the increase in interest rates, and sell government bonds to finance the increased credit demand. On the theoretical side, my model explains these empirical findings and sheds light on the effect of climate change on banks' capital structure. To my knowledge, my model is the first in the credit rationing literature to characterize the interaction among assets. The practical lesson from this chapter

is that, by strategically allocating assets, bank can ensure a stable income and satisfy the needs of the community.

Chapter 4 contributes to the understanding of the role of good governance in disaster relief. First and foremost, the stochastic frontier model offers a benchmark for comparing countries that differ enormously in their economic and natural conditions. Second, by unifying multiple measures of disaster cost into a single estimation model, I find a trade-off between the number of people killed and the economic damage incurred. I show that the rise in efficiency implies a decrease in mortality but an increase in the material damage. Put differently, to be efficient means to be humane in institutions. The third contribution relates to the finding that institutional variables, especially those that reflect good governance, positively predict disaster-relief efficiency. This finding points out that, if a country wants to increase its disaster-relief efficiency, reforming its institutions is a possible way to achieve that goal.

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Curriculum Vitae

Runliang Li was born on November 28th, 1990 in Jinan, Shandong, China. He earned his Bachelor in English from Tianjin University and Bachelor in Finance from Nankai University in 2013. He went to Maastricht University to study the Master in Economic and Financial Research after which he continued to be a PhD student at the Finance Department under the supervision of Prof. dr. Jaap Bos and Dr. Mark Sanders.

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