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Hazardous lending: The impact of natural disasters on bank asset portfolio☆

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ABSTRACT

This paper examines how banks adjust their asset structure in response to changes in loan demand following natural disasters. We demonstrate how banks' asset diversification strategy helps clients smooth consumption and supports local recovery. In the empirical section, we apply the difference-in-differences method and determine that U.S. commercial banks increase real estate lending after disasters and sell government bonds to finance this disaster-driven credit surge. The theoretical section presents a novel multiple-asset dynamic credit allocation model that explains our empirical findings. We use model simulations to predict and quantify the potential impact of climate change on the asset structure and profitability of banks given different scenarios.

1. Introduction

Banks' behavior in response to adverse events, whether economic or non-economic, is of central importance to economic policymaking and financial stability. In this study, we approach this issue from the angle of natural disasters. Specifically, we examine how banks adjust their asset structure in response to changes in loan demand following natural disasters, like extreme weather events. In light of ongoing climate change and pandemics, this issue is highly relevant and is likely to gain more significance in the future.

We establish the empirical relevance of our study by demonstrating that natural disasters influence the composition of loans and securities. We then present a dynamic credit allocation model to illustrate the most important underlying mechanisms and calibrate it to reproduce stylized facts. Using numerical simulations, we investigate the potential impact of climate change on bank balance sheets.

Bank behavior in our study mainly refers to the behavior of asset allocation. Credit allocation behavior is a central topic of banking research and the subject is discussed in much existing literature. Theoretical contributions include Stiglitz and Weiss (1981), Brunnermeier et al. (2012), and Gorton and He (2008). Empirical studies include Hannan and Berger (1991), Angbazo (1997), Asea and Blomberg (1998), Carling and Lundberg (2005), and Zecchini and Ventura (2009).

Natural disasters damage property thereby creating demand for household and firm credit to finance reconstruction and smooth consumption. To the best of our knowledge, there are few existing studies that investigate how banks adjust their asset portfolio composition in response to natural hazards. This study relies on and emphasizes the fact that a diversification strategy to manage natural hazards is important for banks as it follows standard modern banking practices and is easy to understand and implement. It also provides banks with a powerful natural hedge against potentially large losses. By strategically allocating assets between asset classes, banks can better serve the increased loan demand following disasters, and thereby aid economic recovery.

We present empirical facts and a theoretical framework to examine how natural hazards (and anticipation of natural hazards) affect bank asset allocations. For the empirical analysis we use call reports, which contain information regarding all consolidated balance sheet data from U.S. commercial banks over a period of 45 quarters from 2002 to 2013

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and make use of two natural disaster datasets. The Emergency Events Database (EM-DAT) dataset provides detailed natural disaster information such as date, location, type, magnitude, and damage. We then use the Federal Emergency Management Agency (FEMA) records on major disaster declarations in the United States as a reference to check and complete the EM-DAT data.

In our empirical section, we identify the causal effect of natural disasters on bank asset allocations by applying a stacked difference-in-differences (DID) analysis, estimating the impact of the disaster on commercial bank asset quantities. We use data from the 86 most costly natural disasters that occurred between 2001 and 2013 and discover a significant increase in total loans and real estate loans following the disasters, while bank holdings of government bonds decreased. A similar result emerges in a series of heterogeneity analyses and is consistent with previous findings: firms and residents affected by natural disasters increase their demand for loans, (i.e., mortgage), and banks react to this increase by supplying loans financed by the sale of government securities (Cortés, 2017).

In our theoretical section, we develop a dynamic credit allocation model introducing multiple assets to imitate the portfolio composition response. In our model, natural disasters destroy firm fixed capital, leading to a surge in loan demand and an increased borrowing rate. The impact of disasters on banks is then twofold. On one hand, they suffer delayed or defaulted loan repayments because disasters destroy borrower capital and repayment capacity; on the other hand, they have an opportunity to service the increased demand at a higher interest rate, thus improving their profitability.

We calibrate our model to reproduce the key financial ratios we observe in our data under normal conditions and numerically simulate a negative disaster shock on firm capital to replicate our empirical findings. In the simulations, as in our data, we observe that banks increase post-disaster lending at a higher interest rate, and sell government bonds to finance these new loans. Evidently, their ability to do so then depends on pre-disaster reserves and government securities holdings. Therefore, banks and the public can benefit from more robustly funded banks in two ways. First, banks can satisfy the demand for loans and thereby promote an economic recovery. Second, banks can increase their post-disaster revenue to compensate for losses related to disaster-induced defaults.

Finally, we simulate scenarios of climate change to observe how banks respond and reallocate their assets. These simulations show that an increase in the (perceived) probability of disaster due to climate change will be associated with decreased lending, a lower level of capital, less revenue and higher holdings of government bonds in the pre-disaster steady state. In other words, our model predicts that in normal times banks will keep a larger buffer of tradable government securities in anticipation of bigger and more frequent climate-induced shocks in credit demand. Such behavior would be rational and socially optimal, but our simulations also show this reduces bank income and returns-on-equity in normal times. Consequently, such a long-run rational strategy may clash with the interests of short-sighted stock holders thereby possibly making regulatory or supervisory interventions necessary.

Our paper contributes to the existing literature in three ways. First, we use the DID method to demonstrate how banks adjust their asset structure following a natural disaster. Specifically, we determine that banks issue more loans secured by real estate and sell government bonds to finance this increased lending. Second, we extend and generalize the Collier (2020) model to explain how this asset structure change is driven by a disaster-related credit demand shock. To model this, we introduce asset multiplicity and credit demand into a dynamic setting, producing the interactions that we observe. To our knowledge, this aspect of disaster-related banking has not yet been discussed in the existing literature. Third, our calibrations and numerical simulation results enable us to quantify the potential impact of climate change on bank balance sheets via the natural hazard channel. Although the existing literature has proposed that such a link exists, it is a hotly debated topic because few scholars have been able to provide sensible quantitative estimates of such as impact.

The remainder of this paper is as follows: Section 2 positions our work in terms of the relevant literature; Section 3 introduces our data; section 4 reveals how natural disasters affect bank asset allocations; Section 5 presents our theoretical framework, calibrates the model, and compares the model and data moments; Section 6 and 7 then simulate the impact of disaster shocks and climate change; and Section 8 concludes.

2. Positioning in the literature

Our paper relates to several strands of the literature. In terms of the theoretical background, optimal portfolio choice theories date back to Markowitz (1952), Merton (1969), and Samuelson (1969). Theoretical microeconomic models in the optimal credit rationing literature are discussed by Porter (1962), Jaffee and Modigliani (1969), Klein (1970, 1971), Broaddus (1972), Pringle (1974), Sealey (1980), Stiglitz and Weiss (1981), and Slovin and Sushka (1983). Macroeconomic research to understand the role of financial intermediaries has been undertaken by Pagano (1993), Bernanke and Gertler (1989), Carlstrom and Fuerst (1997), Iacoviello (2005), and Brunnermeier et al. (2012). Gorton and He (2008) model and test bank credit cycles in the repeated game framework.

From the development economics perspective, our paper is related to other papers emphasizing the role of financial institutions in natural disaster alleviation and recovery. Toya and Skidmore (2007) reported that countries with more advanced financial systems suffer fewer economic losses following natural disasters. Noy (2009) corroborated the fact that a higher level of domestic credit enhances a country's resilience to disaster shocks, but emphasizes that countries with less open capital accounts are more robust in dealing with natural disasters. Loayza et al. (2009) examined the impact of natural disasters on growth according to disaster and industry type and asserted that the industrial sectors of developing countries are more affected than those in developed countries. This paper looks beyond this literature by focusing on the response of individual banks to natural disasters.

Concerning the micro-level behavior that explains the aforementioned phenomena, this paper is also related to recent literature on credit dynamics during a natural disaster (Berg and Schrader, 2012; Chavaz, 2014; Koetter et al., 2020; Cortés and Strahan, 2017; Dlugosz et al., 2021). For example, Berg and Schrader (2012) showed that credit demand increased after volcanic eruptions in Ecuador and found that bank–firm relationships positively predicted firm access to post-disaster credit. Chavaz (2014) focused on the supply side and showed that local banks of disaster-struck regions possessed more private borrower information than geographically diversified banks. During the 2005 American hurricane season, local banks used loan sales to circumvent capital constraints and satisfy increased firm mortgage demands. Cortés and Strahan (2017) found that banks geographically reallocate funds when local credit demand increases following natural disasters. Moreover, they observed that banks increased the sales of more liquid loans to lessen the impact of the demand shock on the credit supply. Rather than focusing on the geographic distribution of assets, this paper proposes that the reallocation of resources within a bank can smooth its income, which is beneficial to both the bank and the local community.

Most existing models have considered the dynamics of a single aggregated asset rather than the intertemporal interaction between multiple assets. Our paper is related to this literature in the sense that we model the behavior of banks over time in response to exogenous shocks in a dynamic, multiple-asset setting.[1] The need to examine the dynamics of multiple assets stems from the fact that banks change not only their loan volumes but also the composition of their portfolios. The theoretical model in this paper is closely related to Collier (2020), who set up a dynamic lending model and evaluated the impact of disaster-related credit risk on the supply of loans to small enterprises. The model predicted that lenders suffered losses in income and therefore contract credit after big natural disasters, which is supported by the data of a small business lender in Peru after the severe El Niño-related flooding of 1998. Instead of focusing solely on 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 firm capital. By linking the payment shock with the demand shock, our model becomes more general and enables us to understand the behavior of both the demand side and the supply side.

Finally, this paper is also related to the emerging literature that examines the increasingly frequent and more catastrophic climate-related natural disasters.[2]

3. Data and descriptive statistics

In this section, we describe our major datasets and the key variables used to empirically analyze the impact of disasters on bank assets and calibrate the parameters for the theoretical model. The balance sheet items for individual banks are from the call reports, the disaster records are from EM-DAT (Guha-Sapir et al., 2015) and the FEMA website, and state-average interest rates are from the Uniform Bank Performance Reports (the UBPRs). The next two subsections discuss the data collection procedure and variables in detail and present the descriptive statistics.

3.1. Data collection

3.1.1. Bank-level variables

We collect data on loans, securities, deposits, and equity from the call reports of all federally insured commercial banks in the United States.[3] From this source, we extract and compile bank-level variables, including loans secured by real estate, commercial and industrial loans, consumer loans, federal government securities, total loans, total assets, and total equity.[4] Our sample starts in the fourth quarter (Q4) of 2002 and ends in Q4 of 2013, including a total of 45 quarters.

[1] An early contribution that considered the intertemporal relationships between multiple categories of banks' balance sheets is Broaddus (1972). Recent studies that have incorporated large exogenous shocks are Chavaz (2014) and Collier (2020). Recent papers that have empirically discussed bank portfolio management in the context of housing prices and credit crunches, rather than natural hazards, include Ayberk and Önder (2022) and Shikimi (2020).

[2] See, for instance, Rietz (1988), Barro (2006, 2009, 2015), Gabaix (2008), Gourio (2012), and Wachter (2013) who study rare economic disasters. Papers by Allen and Gale (2000), Acemoglu et al. (2015), and Sun (2016) have made helpful progress in exploiting systematic and endogenous shocks.

[3] The call report is officially known as the "Report of Condition and Income". It is a quarterly report on a financial institution's condition and income that is used for various purposes, including assessing the financial health and risk profile of the institution. Definition source: https://cdr.ffiec.gov/cdr/public/cdrhelp/Glossary091505.htm.

[4] Federal government securities include the U.S. Treasury securities and U.S. government agency obligations. When we refer to a "government security" or "government bond," we mean the sum of these two items. We do not, however, include "local government securities," which are issued by states and other political subdivisions in the United States because they have different interest rates according to the Uniform Bank Performance Report's (UBPR's) "Non-interest Income, Expenses and Yields."

The call reports provide us with the balance sheet variables that we use in the main analysis. To identify which banks are affected, we also need the location of each bank's branches. The "Summary of Deposit" is a publicly available annual survey that reports branch-level deposits for all Federal Deposit Insurance Corporation (FDIC)-insured institutions. It records the geographic coordinates, county, and five-digit zip code for each branch. The headquarters of each bank are identified by their FDIC Certificate Number. This dataset thus serves as a link between disasters and banks.

3.1.2. Interest rates and default rates

Interest rates and default rates are mainly used to calibrate parameters. The rates of return on assets are not in the call reports but are recorded in the UBPR. 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."[5] In addition to interest rates, we obtain the net loan loss rates that are used to calibrate the model's default rates from the UBPRs. As individual bank interest rates do not deviate from the state average, we model banks as price takers and assume that interest rates for individual banks are more or less equal for all banks in a state. Arbitrage ensures that interest rates are also highly correlated across bank asset types.[6] It is thus reasonable for us to model the interest rate to be the sum of the common prime lending rate determined by the production sector and the risk premium for specific asset types.

3.1.3. Disasters

We gathered disaster data from two sources. Our first data source is EM-DAT, a comprehensive dataset on the characteristics of disasters. The dataset includes natural disasters of all types worldwide and records their dates, human death tolls, material damages, and geographic locations. We extract disasters in the United States from 2001 to 2013 and selected those with costs in the top 5%, resulting in a total of 86 disasters for the analysis.[7] We matched the location of each disaster with a county and classified the counties into either a treatment or a control group in the DID analysis.

We also looked at the disaster declaration records from FEMA (FEMA) between 2000 and 2015. Each declaration item contains four variables—the date, the state, the type of disaster, and the declaration type. The types are not recorded in a uniform manner. For instance, fires are often recorded along with their locations; hurricanes and tropical storms are used interchangeably; and floods are sometimes recorded alone but are occasionally recorded with other disasters such as winter or severe storms. As FEMA data are not as detailed and well-sorted as EM-DAT data, we only used them as a reference to calculate the disaster probability for each state.

3.2. Descriptive figures and statistics

3.2.1. Bank variables

To provide an overall impression of our sample, we present the summary statistics for the major bank variables in Table 1. Table 1 includes the mean, standard deviation, 10th, and 90th percentile values at the

[5] See UBPR User's Guide, Page III-14, https://www.ffiec.gov/PDF/UBPR/01ubp31a.pdf.

[6] We have checked the development of interest rates and found a parallel trend and a high correlation between all assets.

[7] The EM-DAT also features many non-disasters in which the damage and human impact are very mild, so they would not be considered disasters. As it is not likely that such non-events have a significant impact on local financial markets, we focused on the top 5%. In a robustness check, we extended the cutoff point to 10% and included 167 disasters. The results are similar. Our results are thus representative of the more extreme events.

Table 1

Key Statistics. This table displays statistics for variables using call report data that cover all commercial banks in the United States. All of the variables are in millions of dollars. The mean, standard deviation, 10th percentile, and 90th percentile are based on individual bank–quarter observations. The time horizon is 2002:Q4 to 2013:Q4. Panel A is based on original data that contain all of the banks in the call report. Panel B is based on the sample used for regression analysis (stacked DID), that is, the sample after merging it with events. To reduce the statistical bias, we set the upper limit of total assets in our sample to be the 99th percentile and the remaining values are treated as outliers.

	Average	Standard deviation	10thPercentile	90thPercentile	Observations
Panel A: Banks in the Call Report					
Total Assets	1.334	22.694	0.033	0.679	313,697
Total Loan	0.791	12.270	0.016	0.460	313,697
Cash	0.009	0.041	0.001	0.015	308,769
Real Estate Loan	0.458	7.164	0.008	0.341	313,696
C&I Loan	0.141	2.265	0.001	0.070	313,697
Individual Loan	0.121	2.325	0.001	0.022	313,696
Government Securities	0.020	0.143	0.000	0.038	308,769
Deposit	0.665	10.113	0.022	0.455	313,696
Total Equity	0.042	0.276	0.004	0.061	308,769
Panel B: Banks in the Sample					
Total Assets	2.680	17.001	0.039	1.258	171,596
Total Loan	1.674	10.748	0.018	0.804	171,596
Cash	0.014	0.055	0.001	0.020	165,383
Real Estate Loan	0.969	5.887	0.009	0.590	171,596
C&I Loan	0.355	2.460	0.002	0.128	171,596
Individual Loan	0.195	1.745	0.001	0.034	171,596
Government Securities	0.031	0.155	0.000	0.049	165,383
Deposit	1.418	8.568	0.026	0.830	171,596
Total Equity	0.060	0.235	0.004	0.087	165,383

bank–quarter level. Panel A shows the summary statistics for all of the banks in the call reports from 2002:Q4 to 2013:Q4. Panel B is based on the sample we use for the empirical analysis; we provide more explanation about the formation of this sample in the next section.[8]

The large standard deviations in both panels indicate that the samples include heterogeneous banks throughout the country. Such heterogeneity distorts the mean to a large extent. As we can observe from the leverage ratio (i.e., the ratio of equity to assets), the values at the 10th and 90th percentiles are both about 10%, a common value for banks, but the ratio obtained using the mean values of equity and assets is only about 3%. We will thus perform a heterogeneity analysis for bank size in the following empirical section. Furthermore, the statistics reveal that loans secured by real estate account for more than 50% of all loans. Since this type of loan is secured by real estate, it is considered safer than other types of loans, which have other kinds of collateral or no collateral at all.[9]

3.2.2. Disaster frequency

By examining disaster records in both the EM-DAT and FEMA datasets, we find that, first, natural disasters are very prevalent in the United States. There are, however, regional differences. In the western territory, wildfires are the greatest 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 recorded natural disasters in the United States during 2001 and 2013, disasters that cause more than $1 billion in losses account for only 3.51%, while zero-cost disasters are about 85.47%. Among these zero-cost events, around 30.71% are wildfires, and 20.08% are tornados. Among the top 5% of the most costly disasters, around 90% are floods and hurricanes. Since the mechanism underlying disasters and banks' portfolio adjustment is similar for different types of disasters, we will not consider disaster type in the theoretical model. However, we do perform a heterogeneity analysis in the empirical section and find that the results are similar for different types of events.

To give a better impression of the type and frequency of disasters, we plot the following figures based on FEMA disaster records. Fig. 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 floods, whereas wildfires are the most common natural disaster in states like Texas, California, and Wyoming.

In addition, based on the major disaster declarations, we calculate the quarterly probability of a natural disaster occurring in each state. For example, Louisiana declared 20 major disasters between 2000 and 2015 and so the average quarterly frequency of a natural disaster occurring is $20/(16 \times 4) = 31.25\%$. Fig. 2 plots the histogram of the number of disasters. Based on this graph, we calculate the average quarterly disaster probability for each state to be approximately 22.85%. This value will be used as the bank's subjective perception of the disaster probability when we calibrate the model.[10]

4. Empirical analysis

This section details bank responses to natural disaster shocks and provides empirical evidence for our theoretical study. We observe that natural disasters cause banks to increase loans secured by real estate and decrease holdings in government bonds. We also find that commercial loans and consumer loans either increase or remain unchanged. Overall, the total amount of loans increases after a natural disaster. In addition to the main analysis, we perform a series of robustness checks

[8] We set the upper limit of total assets in our sample to the 99th percentile to avoid the effect of large national banks on both the summary statistics and regression coefficients.

[9] For a more detailed explanation of the role of collateral, see Gan (2007) and Chaney et al. (2012).

[10] Knowing the exact value of a 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, 2009, 2015; Gabaix, 2008; Gourio, 2012; Wachter, 2013).

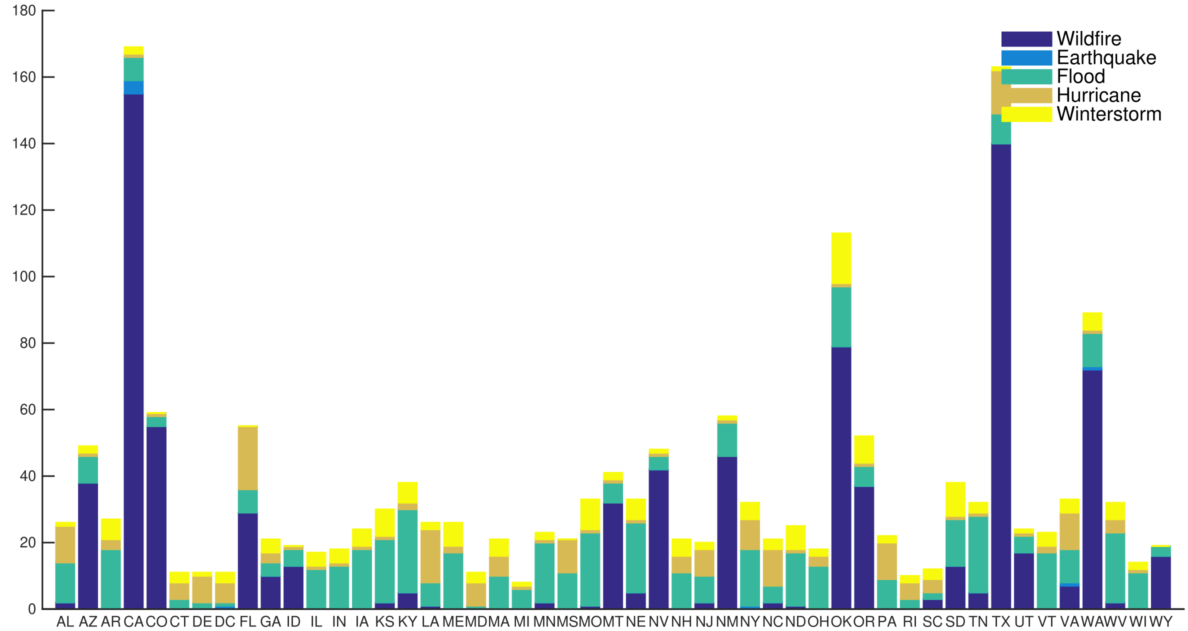

Fig. 1. Number of Natural Disaster Declarations (2000 to 2015). This figure displays the frequency of each type of the five disasters for every state. The data include disaster declarations available on the FEMA website (FEMA).

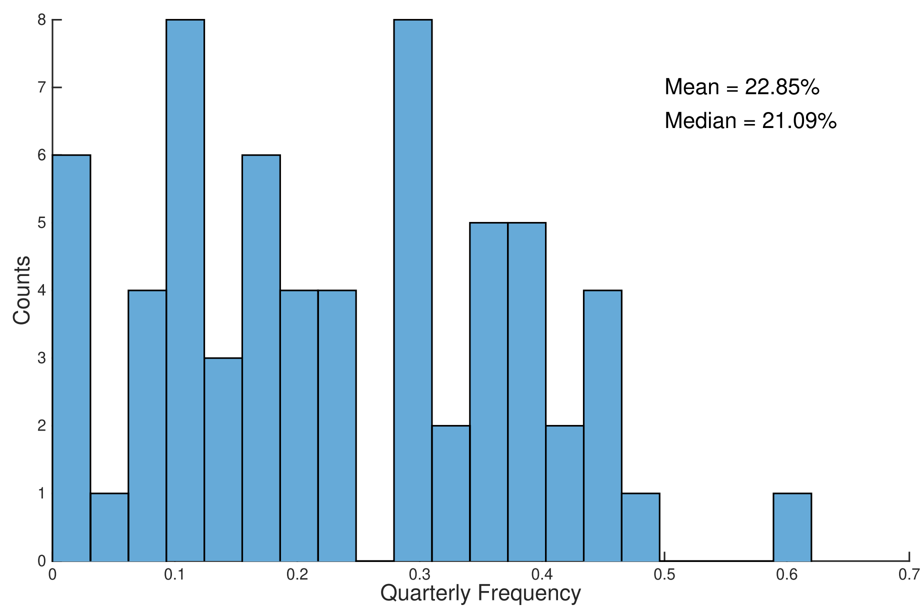

Fig. 2. Distribution of Quarterly Frequency of Major Disasters. This figure exhibits the histogram of the average quarterly frequency of "major disasters" across different states and territories in the United States. The data come from FEMA. Based on this histogram, we calculate the average disaster frequency to be 22.85%. This value will be used in our model as the bank's perceived disaster probability to calibrate the model.

regarding heterogeneity in disaster type, bank size, and macroeconomic background.

4.1. Methodology

To identify the causal effect of a natural disaster on a bank's balance sheets, we rely on DID analysis, the key task of which is to identify if banks are affected or not by a disaster. Our procedure is as follows:

For each event, the EM-DAT records its geographic coordinates, which enables us to identify the affected county.[11] We then use the Summary of Deposit dataset to identify which bank branches are located in the affected county; these banks are classified as the treatment group. Finally, banks in the same state with unaffected branches are used as the control group.

[11] We use the inpolygon function in MATLAB to perform this task. We can also identify the neighbor counties (i.e., counties sharing part of the same border) of the affected county. Later, we perform a robustness check to treat the neighbor counties also affected. The impact becomes smaller, though still significant.

Table 2
Impact of Disasters on Bank Assets. This table presents the baseline results of stacked DID analysis on the impact of a natural disaster on bank-level assets using a ±1-year event window. We include 86 disasters with costs in the top 5% based on the EM-DAT database. We analyze balance sheet values (in millions of dollars) of real estate loans (*RS Loan*), commercial and industrial loans (*CI Loan*), consumer loans (*CS Loan*), government securities (*Security*), and total loans (*Total Loan*). The time horizon is 2002:Q4 to 2013:Q4. We treat a bank to be affected if it has branch(es) in the affected county, and the unaffected banks are in the same state but have no branch in the affected county. We include county, time, bank, and event fixed effects to account for regional and macroeconomic conditions, bank characteristics, and event-specific effects. Standard errors are reported in parentheses. ***, **, * denote significance at 1%, 5% and 10%, respectively.

	RS Loan	CI Loan	CS Loan	Security	Total Loan
Affected × Post	0.028***	0.013***	0.002***	−0.004***	0.045***
	(0.004)	(0.001)	(0.001)	(0.001)	(0.004)
Size	0.391***	0.088***	0.020***	0.018***	0.522***
	(0.003)	(0.001)	(0.001)	(0.001)	(0.004)
Capital Adequacy	0.645***	0.263***	0.025***	0.042***	1.008***
	(0.023)	(0.008)	(0.005)	(0.005)	(0.030)
Liquidity	−0.014	−0.015	0.027***	−0.048***	−0.015
	(0.028)	(0.009)	(0.006)	(0.007)	(0.036)
County FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Event FE	Yes	Yes	Yes	Yes	Yes
Observations	165,383	165,383	165,383	165,383	165,383
R-squared	0.955	0.947	0.948	0.901	0.964

In our baseline analysis, we select the most expensive 5% recorded disasters in the EM-DAT dataset. This cutoff level leads to 86 events affecting multiple counties during the 45 quarters that our dataset spans. We later use the 10% cutoff level for a robustness check.[12] We examine the average effect of all of the selected events using the following equation:

$$y_{bcet} = \beta_0 + \beta_1 Affected_{ce} \times PostDate_{et} + \gamma X_{bect} + CountyFE + TimeFE + BankFE + EventFE + \epsilon_{bect}, \tag{1}$$

where y_{bcet} represents the quantity of an asset of bank b located in county c at quarter–year t for event e. *Affected* equals 1 if a county is affected and 0 otherwise. *PostDate* equals 1 if the observation date t is after the end date of the event and 0 if it is before the start date. The county, time, bank, and event fixed effects capture unobservable regional and macroeconomic conditions, bank characteristics, and event-specific effects. In line with Koetter et al. (2020), we control in X_{bcet} for bank-specific variables including bank size (total assets), capital adequacy (total equity/total assets), and liquidity (non-interest-bearing cash/total assets). As we have multiple events, our analysis is, in essence, a stacked DID.

4.2. Empirical results

We present the baseline results of our DID analysis in Table 2. The results show that affected banks increase all three loan categories and decrease government security holdings following a disaster, which is consistent with Cortés (2017). The coefficients are both statistically and economically significant. For example, banks in affected counties increase real estate lending, on average, by $0.028 million more than those in unaffected counties. Compared to the mean value in Table 1, this amount is about 3% of outstanding real estate loans. Government securities decrease by $4 thousand, which is about a 13% decrease compared to its mean value in the summary statistics.

We subsequently perform a series of heterogeneity analyses. We investigate whether banks react differently to different disasters, as shown in Table 3, wherein we estimate the effects of four types of disasters: floods, storms, cold snow and freezing rain, and drought. On the one hand, banks are similar in that they increase real estate and commercial loans after floods, storms, and cold snow. On the other hand, the change in government securities is not significant following a flood.[13]

Table 4 presents the estimates by bank size. We divide banks into 10 groups using the deciles of total assets. Interestingly, we find that only the smallest and largest banks significantly increase their real estate lending, whereas for government securities, banks in most groups significantly decrease their holdings. On the one hand, these results demonstrate that selling government bonds is a common practice of banks' liquidity management to satisfy increased loan demand. On the other hand, such heterogeneous behaviors in real estate lending may indicate that either small or big banks have advantage in meeting the increased credit demand, possibly due to the advantages of either processing soft information or handling big data; but the middle-sized banks do not have such advantages. The effect of bank size heterogeneity is an important question for future research.

Table 5 present the results of our estimations by macroeconomic stage. One concern is that with the development of fintech, the landscape of banks might be changing, which might lead to different responses over time. We thus separate our sample into three sub-periods (i.e., 2002 to 2006, 2007 to 2009, and 2010 to 2013). These three sub-periods correspond roughly to the developmental stages of fintech, namely, no fintech, fintech beginning (with a disturbance from the financial crisis), and expansion. We find no significant differences in banks' response to disasters. In Table 6, we extend the cutoff level of disaster cost from top 5% to top 10% and find the results are similar.

[12] We chose these large-scale disasters to make sure that they are *ex-ante* unpredictable and exogenous. Firms and banks already have a subjective belief about the risks in their region and are therefore prepared, to some extent, for more mundane events. In addition, only relatively large disasters generate a significant and regionally correlated shock affecting productive and residential capital of nearly all local firms and residents simultaneously. Consequently, only relatively large events can reasonably be assumed to cause significant loan defaults, an increase in credit demand, and an increase in borrowing costs.

[13] A satisfactory explanation may require investigation of more detailed data, which is out of the scope of this paper. We conjecture the reason is mainly due to the characteristics of banks in the flooded regions, not necessarily due to the disaster type.

Table 3
Impact of Disasters on Bank Assets According to Disaster Type. This table presents the results of stacked DID analysis on the impact of natural disasters on assets by disaster type. We have four types of disasters: floods, storms, cold snow and freezing rains, and droughts, where the storm category originally contains tropical storms and cyclones, windstorms, and thunderstorms. We include 86 disasters with costs in the top 5% based on the EM-DAT database. We analyze the balance sheet values (in millions of dollars) of real estate loans (*RS Loan*), *CI Loan*, consumer loans (*CS Loan*), government securities (*Security*), and total loans (*Total Loan*). The time horizon is 2002:Q4 to 2013:Q4. We treat a bank to be affected if it has branch(es) in the affected county, and the unaffected banks are in the same state but have no branch in the affected county. We only include the coefficients of Affected × Post. The columns represent disaster types, and for each type, the R-squared is the average R-squared value of the regressions on different assets. We include county, time, bank, and event fixed effects to account for regional and macroeconomic conditions, bank characteristics, and event-specific effects, respectively. Standard errors are reported in parentheses. ***, **, * denote significance at 1%, 5% and 10%, respectively.

Disaster	Flood	Storm	Cold Snow	Drought
RS Loan	0.046***	0.029***	0.039***	0.003
	(0.008)	(0.003)	(0.013)	(0.032)
CI Loan	0.017***	0.011***	0.030***	−0.003
	(0.004)	(0.002)	(0.005)	(0.016)
CS Loan	0.020***	2.88e-04	0.014***	−0.004
	(0.003)	(0.001)	(0.002)	(0.010)
Security	0.002	−0.004***	−0.012***	−0.006
	(0.003)	(0.001)	(0.003)	(0.012)
Total Loan	0.085***	0.044***	0.082***	−0.006
	(0.012)	(0.005)	(0.016)	(0.051)
County FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Event FE	Yes	Yes	Yes	Yes
Observations	27,723	32,039	13,505	3470
R-squared	0.956	0.964	0.976	0.983

This is not surprising as the top 10% disasters can all cause severe damage. In Table 7, we also treat the neighbors of the affected county in each disaster as affected. Compared to Table 2, we find the estimates become smaller, meaning that the most significant changes are in the affected county, not their neighbors.

In the next section, we provide a theoretical model to explain our empirical findings, particularly focusing on the tendency of banks to extend credit and sell government bonds. Our model indicates that disasters stimulate community loan demand to aid reconstruction by destroying capital. Moreover, the assumption that disasters are correlated with loan defaults enables our model to explain why all categories of loans increase following a natural disaster.

5. Theoretical model

In this section, we set up a theoretical model to explain banks' asset allocation behavior during disasters. We then calibrate the model parameters and compare the key financial ratios implied by the model with real data. This comparison shows that our model is able to reproduce the data reasonably well, and sets the stage for the simulation of a natural disaster and climate change scenarios in the following sections.

We firstly compile a single-asset model to introduce our main variables and show bank lending decision-making strategies based on loan conditions, disaster probability, and interest rates (Model 1). We then allow for multiple assets, which enables us to generate interactions between assets when a disaster strikes (Model 2). Our model contains two economic agents: banks and firms, which represent the supply and demand side of funds, respectively. Collectively, firms have an infinite demand at a market borrowing interest rate, which is determined by the marginal productivity of capital in production and investment. Individual banks then decide how much to lend based upon this interest rate. A disaster is modeled to destroy firm capital, thus increasing the marginal capital productivity, the borrowing interest rate, and possibly the default rate of existing loans. It is assumed that individual banks aim to maximize shareholder value and endogenously react to this shock by adjusting their asset structures. The single-asset banking model is based mainly on the model by Collier (2020). In the following subsections, we first present the basic setup, then add the production sector to the one-asset model, and finally extend it to a multi-asset setting.

5.1. Basic model setup

Following Collier (2020) we introduce 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, $\widetilde{L}_t$, is paid back at the end of the period due to default.[14] We model this relationship as follows:

$$\widetilde{L}_t = (1 - \xi_t)L_t, \tag{2}$$

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

$$\xi_t = \overline{\xi} + \epsilon_t^{\xi}, \tag{3}$$

where ϵ_t^{ξ} captures unexpected shocks and $\overline{\xi}$ represents the bank's expected default rate as follows:

$$\overline{\xi} = p(\mu + \xi^*) + (1 - p)\mu = \mu + p\xi^*, \tag{4}$$

where μ represents the default rate in normal times, ξ^* is the average default rate increment when a disaster occurs and the bank expects the disaster to happen with probability p. We introduce this probability to

[14] Since 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 newly issued loans, a flow variable. The latter then represents a choice variable, as banks determine how many new loans they issue every period. However, it is in fact equivalent to assume that the bank decides on total outstanding loans L_t 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 decide the level of L_t makes the theory consistent with the empirical analysis.

Table 4

Impact of Disasters on Bank Assets according to Bank Size. This table presents the results of stacked DID analysis on the impact of natural disasters on assets by bank size. We use deciles of total assets to divide banks into 10 groups. We include 86 disasters with costs in the top 5% based on the EM-DAT database. We analyze balance sheet values (in millions of dollars) of real estate loans (*RS Loan*), *CI Loan*, consumer loans (*CS Loan*), government securities (*Security*), and total loans (*Total Loan*). The time horizon is 2002:Q4 to 2013:Q4. We treat a bank to be affected if it has branch(es) in the affected county and the unaffected banks are in the same state but have no branches in the affected county. We only include the coefficients of Affected × Post. The columns represent bank size, and for each group, the R-squared is the average R-squared value of regressions on different assets. We include county, time, bank, and event fixed effects to account for regional and macroeconomic conditions, bank characteristics, and event-specific effects. Standard errors are reported in parentheses. ***, **, * denote significance at 1%, 5%, and 10%, respectively.

Size	1	2	3	4	5	6	7	8	9	10
RS Loan	3.677e-04**	−2.145e-04	1.230e-04	3.355e-04	−4.337e-04	−0.001**	−0.001	−0.001	−0.002	0.034*
	(1.646e-04)	(1.932e-04)	(2.448e-04)	(2.897e-04)	(3.425e-04)	(4.149e-04)	(0.001)	(0.001)	(0.002)	(0.020)
CI Loan	1.240e-04	1.622e-05	1.137e-04	−1.756e-04	0.001***	−0.000**	0.001***	−2.552e-04	−1.160e-04	0.024***
	(8.699e-05)	(9.492e-05)	(1.263e-04)	(1.444e-04)	(1.797e-04)	(2.146e-04)	(2.743e-04)	(3.602e-04)	(0.001)	(0.008)
CS Loan	9.770e-05*	1.836e-04***	2.933e-04***	−5.525e-05	9.577e-05	−3.007e-05	−1.792e-04	2.291e-04	0.001***	−0.002
	(5.238e-05)	(6.204e-05)	(5.396e-05)	(6.698e-05)	(8.751e-05)	(9.114e-05)	(1.242e-04)	(1.789e-04)	(3.605e-04)	(0.006)
Security	−3.683e-04**	−2.129e-04	−6.248e-05	−4.255e-04*	−0.001***	−1.493e-06	−4.913e-04	−0.001*	−0.004***	−0.010
	(1.635e-04)	(1.917e-04)	(2.153e-04)	(2.464e-04)	(2.916e-04)	(3.451e-04)	(4.297e-04)	(0.001)	(0.001)	(0.006)
Total Loan	0.001***	−8.148e-05	0.001**	1.843e-04	3.801e-04	−0.002***	−8.633e-05	−0.001	−0.001	0.055**
	(2.146e-04)	(2.308e-04)	(2.727e-04)	(3.245e-04)	(3.849e-04)	(4.625e-04)	(0.001)	(0.001)	(0.002)	(0.025)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Event FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,196	17,162	17,157	17,160	17,145	17,112	17,079	16,966	16,774	11,632
R-squared	0.895	0.910	0.929	0.933	0.930	0.928	0.932	0.932	0.923	0.947

Table 5

Impact of Disasters on Bank Assets according to Macroeconomic Stage. This table presents the baseline results of stacked DID analysis on the impact of natural disasters on bank-level assets by macroeconomic stage. We divide the whole period into three sub-periods, 2002 to 2006, 2007 to 2009, and 2010 to 2013. These three sub-periods correspond roughly to the development stages of fintech, namely, no fintech, beginning (with a disturbance by the financial crisis), and expansion. We include 86 disasters with costs in the top 5% based on the EM-DAT database. We analyze balance sheet values (in millions of dollars) of real estate loans (*RS Loan*), *CI Loan*, consumer loans (*CS Loan*), government securities (*Security*), and total loans (*Total Loan*). The time horizon is 2002:Q4 to 2013:Q4. We treat a bank to be affected if it has branch(es) in the affected county, and the unaffected banks are in the same state but have no branch in the affected county. We only include coefficients of Affected × Post. We include county, time, bank, and event fixed effects to account for regional and macroeconomic conditions, bank characteristics, and event-specific effects. Standard errors are reported in parentheses. ***, **, * denote significance at 1%, 5%, and 10%, respectively.

	RS Loan	CI Loan	CS Loan	Security	Total Loan
Panel A: 2002 to 2006					
Affected × Post	0.022***	0.015***	0.001	−0.001	0.040***
	(0.007)	(0.003)	(0.002)	(0.002)	(0.010)
Observations	33,649	33,649	33,649	33,649	33,649
R-squared	0.974	0.965	0.966	0.887	0.980
Panel B: 2007 to 2009					
Affected × Post	0.014***	0.001	0.008***	−0.006***	0.022***
	(0.005)	(0.002)	(0.002)	(0.002)	(0.007)
Observations	33,380	33,380	33,380	33,380	33,380
R-squared	0.989	0.988	0.973	0.894	0.992
Panel C: 2010 to 2013					
Affected × Post	0.027***	0.011***	0.001	0.001	0.044***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)
Observations	98,354	98,354	98,354	98,354	98,354
R-squared	0.987	0.965	0.980	0.957	0.986
County FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Event FE	Yes	Yes	Yes	Yes	Yes

Table 6

Impact of Disasters on Bank Assets with More Disasters. This table presents our baseline results of stacked 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 10%, compared to the 5% cutoff point in the main analysis, based on the EM-DAT database. We analyze balance sheet values (in millions of dollars) of real estate loans (*RS Loan*), *CI Loan*, consumer loans (*CS Loan*), government securities (*Security*), and total loans (*Total Loan*). The time horizon is 2002:Q4 to 2013:Q4. We treat a bank to be affected if it has branch(es) in the affected county, and the unaffected banks are in the same state but have no branch in the affected county. We include county, time, bank, and event fixed effects to account for regional and macroeconomic conditions, bank characteristics, and event-specific effects. Standard errors are reported in parentheses. ***, **, * denote significance at 1%, 5%, and 10%, respectively.

	RS Loan	CI Loan	CS Loan	Security	Total Loan
Affected × Post	0.031***	0.010***	2.328e-04	−0.004***	0.042***
	(0.004)	(0.001)	(0.001)	(0.001)	(0.004)
Size	0.419***	0.077***	0.023***	0.015***	0.540***
	(0.003)	(0.001)	(0.001)	(0.001)	(0.004)
Capital Adequacy	0.842***	0.235***	0.045***	0.043***	1.198***
	(0.022)	(0.005)	(0.004)	(0.004)	(0.026)
Liquidity	0.140***	−0.016**	0.002	−0.053***	0.115***
	(0.029)	(0.006)	(0.005)	(0.005)	(0.033)
County FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Event FE	Yes	Yes	Yes	Yes	Yes
Observations	300,961	300,961	300,961	300,961	300,961
R-squared	0.926	0.941	0.923	0.890	0.943

simulate different climate change scenarios using different values of disaster probability p in the sections below. For now, it suffices to note that a higher disaster probability implies a higher expected default rate.

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

Table 7
Impact of Disasters on Bank Assets with Neighbors Treated as Affected. This table presents our baseline results of stacked 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 costs are at the top 5% based on the EM-DAT database. We analyze balance sheet values (in millions of dollars) of real estate loans (*RS Loan*), *CI Loan*, consumer loans (*CS Loan*), government securities (*Security*), and total loans (*Total Loan*). The time horizon is 2002:Q4 to 2013:Q4. We treat a bank to be affected if it has branch(es) in the affected county and its neighbor counties, and the unaffected banks are in the same state but have no branch in the affected county. We include county, time, bank, and event fixed effects to account for regional and macroeconomic conditions, bank characteristics, and event-specific effects. Standard errors are reported in parentheses. ***, **, * denote significance at 1%, 5%, and 10%, respectively.

	RS Loan	CI Loan	CS Loan	Security	Total Loan
Affected × Post	0.012***	0.006***	0.002***	−0.001**	0.020***
	(0.002)	(0.001)	(0.001)	(0.000)	(0.003)
Size	0.353***	0.086***	0.023***	0.019***	0.483***
	(0.003)	(0.001)	(0.001)	(0.001)	(0.004)
Capital Adequacy	0.715***	0.268***	0.028***	0.048***	1.085***
	(0.021)	(0.006)	(0.007)	(0.005)	(0.026)
Liquidity	−0.012	−0.011	0.027***	−0.042***	−0.011
	(0.024)	(0.007)	(0.007)	(0.005)	(0.030)
County FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Event FE	Yes	Yes	Yes	Yes	Yes
Observations	231,621	231,621	231,621	231,621	231,621
R-squared	0.950	0.941	0.941	0.892	0.959

$$R_t = r_t\widetilde{L}_t - r_t^D D_t - h(L_t) - \xi_t L_t, \tag{5}$$

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

$$r_t = r_t^* + \kappa, \tag{6}$$

with r_t^* is the basic equilibrium lending rate determined on the production side, introduced below, and κ is the risk premium of the loan. In the model by Collier (2020), the basic borrowing/lending interest rate, r_t, is a given parameter. In our model, however, we let it be determined by the production sector to introduce a second channel through which natural disasters can enter the banks' decision-making. By destroying capital, natural disasters increase 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.[15] We can relate deposits D_t to the interest rate r_t^D and a constant N, which controls the size of the balance sheet[16]:

$$D_t = N(1 + r_t^D) \tag{7}$$

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

$$L_t = D_t + E_t \tag{8}$$

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 to reflect that process is as follows:

$$h(L_t) = \eta L_t + \frac{\Psi}{2}L_t^2, \tag{9}$$

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 many loans, it becomes more difficult to search, evaluate, and monitor new borrowers and has increasingly invasive interventions from the banking authorities when its leverage becomes too high.[17] The next period's equity is current equity less dividend payments plus income as follows:

$$E_{t+1} = (1-\nu)E_t + R_t, \tag{10}$$

where ν is the dividend rate. Finally, the bank's problem is maximizing its overall dividend payments discounted by a time discount factor γ:

$$\max_{L_t} \Pi_0 = \sum_{t=0}^{\infty} \gamma^t \mathbb{E}[\nu E_t], \quad 0 < \gamma < 1. \tag{11}$$

To complete the model, we need to introduce the demand side for loans, that is, the production sector. We assume a mass of price-taking banks and firms such that the demand for a single bank's loans is infinite at the market-determined interest rate. This rate must be equal to firms' marginal productivity of capital.

[15] From an empiricist's point of view, the interest rate is persistent. Especially for loans, both banks and customers cannot 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 $\epsilon_t \sim N(0, \sigma^2)$ is a random shock. In the simulations that follow, to conform to reality and to improve the readability of the graphs, we set $\rho > 0$, which means banks continue to charge a higher interest rate during some quarters after the disaster. To keep the exposition of the model clean, however, we set $\rho = 0$ here.

[16] This is also an extension compared to the model by Collier (2020) that simply sets deposits to be the difference between assets and equity. In this way, we can add a shock to deposits when we have reason to believe that households and banks react to disasters by withdrawing deposits or changing the deposit rate. We will not dwell on this experiment here, 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. (2021) detailed how banks' decision-making delegation affected their ability to set deposit rates and the consequences of the deposit level and economic recovery. Second, we did not find robustly significant empirical evidence on the change in deposit after disasters.

[17] In Collier (2020), the author explicitly models the regulation cost as a step function that remains 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 numerical computations below and is not important to our model's main mechanism.

5.2. Introducing firms

As a disaster affects the whole economy in an affected location, 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 the business cycle model of Gourio (2012); they produce output using a Cobb–Douglas production function as follows:

$$Y_t = AK_t^{\alpha}, \tag{12}$$

where A is productivity level, also known as the total factor productivity. Capital is accumulated according to the law of motion for production capital as follows:

$$K_{t+1} = (1-\delta_t)K_t + \varphi\left(\frac{I_t}{K_t}\right)K_t, \tag{13}$$

where δ_t is the depreciation rate, I_t is the demand for funds, and $\varphi\left(\frac{I_t}{K_t}\right)$ is a function describing capital adjustment costs.[18] A disaster can now be introduced into the model as a sudden increase in the capital depreciation rate:

$$\delta_t = \overline{\delta} + \epsilon_t^{\delta}. \tag{14}$$

If ϵ_t^{δ} and ϵ_t^{ξ} are positively correlated, then this means that disasters indeed lead to defaults of existing loans. Finally, firms maximize profit over time according to the following equation:

$$\max_{I_t,K_{t+1}} \Pi_0^{Firm} = \sum_{t=0}^{\infty}\beta^t\mathbb{E}[Y_t - I_t - r_t^* K_t], \quad 0<\beta<1, \tag{15}$$

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

$$1 + r_t^* = \varphi'\left(\frac{I_t}{K_t}\right)\left(\frac{1-\delta_t+\varphi\left(\frac{I_{t+1}}{K_{t+1}}\right)}{\varphi'\left(\frac{I_{t+1}}{K_{t+1}}\right)} + \alpha\frac{Y_{t+1}}{K_{t+1}} - \frac{I_{t+1}}{K_{t+1}}\right). \tag{16}$$

Equation (16) shows that if disasters increase the depreciation rate of firm capital, this endogenously drives up the interest rate and, by assumption, affects the default rate. The increase in default rate subsequently leads banks to adjust their capital structure. The model, however, still cannot explain the interactions among different asset types after disasters. For this, we need to make a further extension to incorporate multiple assets.

5.3. Banks with multiple assets

Having established the single-asset model, we can slightly enrich the model to allow for interactions between multiple assets.[19] Note that each asset now has its own default rate (i.e., zero for government bonds), interest rate, and cost function. Net income then includes the sum of the interest income of all assets as follows:

$$R_t = \sum_{i=1}^{n} r_{it}\widetilde{L}_{it} - r_t^D D - h(L_t) - \sum_{i=1}^{n}\xi_{it}L_{it}, \tag{17}$$

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

$$r_{it} = r_t^* + \kappa_i, \tag{18}$$

where the bank's lending rate 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 costs for the bank are then given by the sum of individual costs[20]:

$$h(L_t) = \sum_{i=1}^{n}\eta_i L_{it} + \frac{\psi_i}{2}L_{it}^2. \tag{19}$$

Finally, the balance sheet identity becomes the following:

$$\sum_{i=1}^{n} L_{it} = D_t + E_t. \tag{20}$$

With these simple extensions, Model 2 now captures 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 among only two assets.

5.4. Steady state and propositions

The two models allow us to derive the steady-state equilibrium in which the following propositions hold:

Proposition 1. *The level of total loans increases with the interest rate and decreases with the default rate and disaster probability.*

Proof. *At the steady state, the level of aggregated loans L is a constant and the interest rate and default rate are equal to their mean values,* $\overline{r}$ *and* $\overline{\xi}$. *Solving the steady states of Model* 1, *we find*:

$$L = \frac{[(1-\overline{\xi})r - \eta - \overline{\xi} - \nu] + \sqrt{[(1-\overline{\xi})r - \eta - \overline{\xi} - \nu]^2 - 2\psi(r^D - \nu)D}}{\psi}. \tag{21}$$

After taking the first derivative, *we have* $\frac{\partial L}{\partial \overline{r}} > 0$, $\frac{\partial L}{\partial \overline{\xi}} < 0$, *and* $\frac{\partial L}{\partial p} < 0$. *Therefore, the amount of loans is positively related to the interest rate and negatively related to the default rate. More detailed derivations are shown in the 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 default 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. *If a bank has two assets and 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*:

$$L_1 = \frac{[(1-\overline{\xi}_1)r_1 - \eta_1 - \overline{\xi}_1] - [(1-\overline{\xi}_2)r_2 - \eta_2 - \overline{\xi}_2] + \psi_2(D+E)}{\psi_1+\psi_2}. \tag{22}$$

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* $\frac{\partial L_1}{\partial \overline{r}_1} > 0$, *while* $\frac{\partial L_1}{\partial \overline{r}_2} < 0$. *Therefore, when a disaster increases the demand and the interest rate of one asset* (*e.g., mortgage loans*)*, facing its budget constraint, a bank will decrease the holdings of another asset* (*e.g., government securities*)*. We include detailed derivations in the Appendix.*

These propositions and the corresponding proofs state the main results of our theoretical model. In the following subsection we will calibrate our model parameters and illustrate these two propositions more vividly with impulse response graphs.

[18] Here we follow the convention of business cycle literature and specify the capital adjustment function to be $\varphi(\frac{I_t}{K_t}) = \frac{I_t}{K_t} - \frac{\iota}{2}(\frac{I_t}{K_t} - \delta)^2$. It is therefore an increasing and concave function.

[19] In the quantitative analysis, we examined four distinct asset classes, (i.e., loans secured by real estate, commercial and industrial loans, consumer loans, and government securities).

[20] We allow for different levels of asset-specific origination costs. The purchase of a government security in the market is likely to involve significantly lower costs than the origination of a new commercial loan.

Table 8
Calibrated Parameters. *This table repor*ts our calibrated parameters. The interest rate premium and components of default rates are based on the average interest rate and default rate reported in the UBPR. We have data on real estate loans (*RS*), commercial loans (*CI*), and consumer loans (*CS*). Since the net loss data for government securities are not available, we set the default rate of government securities (*GS*) to zero. We fix the interest rates on deposits and government bonds and let the interest rates of other assets be the sum of the basic equilibrium rate and the corresponding risk premiums. Parameters that cannot be directly 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 default rate (%)	μ	2	0.5	2	3	0	match UBPR data
Disaster time default 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 return on equity 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

5.5. Calibration and simulation

We calibrate the model using quarterly data for commercial banks. Some values are calculated directly from real data; others are chosen such that the steady-state values of our key financial variables match the average data statistics. Table 8 summarizes the calibrated parameters for our two models.

The default rate of an outstanding loan equals one less the loan's net loss rate. For each type of loan, net losses are reported in the UBPR as year-to-date (YTD) net losses.[21] In our calibration, we use one minus the mean of a loan's net losses divided by the notional amount as the expected value of the default rate ($\bar{\xi}$). We manually assign the default rate of government securities to zero.

The time discount factors for banks and firms, γ and β, are both set to 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 rate over time and across states and use this value as the interest rate (denoted $\bar{r}_i$) of this asset. Since at equilibrium, the basic borrowing rate determined by firms 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 are sourced 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 following subsection. Other parameters are also calibrated to match the ratios of key variables. 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 8 shows that real estate loans have the highest credit quality among the three types of loans, as is indicated by the fact that it has the lowest average default rate. Every quarter, the default rate for real estate loans is around 0.5%. Commercial and industrial loans have the lowest credit quality, with an average default rate of 3%. This difference reflects the role of collateral in promoting timely loan repayments and validates why real estate lending represents the biggest lending business of banks (Gan, 2007; Chaney et al., 2012).

These calibrated parameters demonstrate that our model can generate key financial ratios that are close to real data. We can now examine the model's quantitative performance. We first compare some key financial ratios generated by the model, with ratios based on real data. Then, we perform simulations to examine the effects of asset price changes after a disaster.

5.6. Data vs. model moments

Table 9 shows the statistics of key financial ratios. The left panel shows ratios calculated based upon the call report data. To avoid extreme values caused by bank size, we select banks with total assets between the 25th and 75th quantiles. The ratios in the right panel are based on our numerical model simulations. The simulated values are the average statistics derived from Monte Carlo simulations, drawing random occurrences of capital depreciation shock (ϵ_t^δ) distribution. Each of the 5000 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. Except for the capital ratio, other financial ratios vary greatly between banks, confirming the diversity of banks' business models. Given the huge deviations in the real data, the ratios generated by our model all fall within the reasonable domain.

To further reduce concerns that the previously simulated financial ratios are sensitive to the choice of parameter values, we perform a number of sensitivity tests. We select the parameters that cannot be directly inferred from real data and for which empirical evidence is scarce. These parameters include the components in the cost function (η and ψ), the time preferences of banks and firms (γ and β), and the constant scale parameter, N, that determines the size of the balance sheet. We increase or decrease them by 10% and compare the key financial ratios with the medians of the baseline model and real data. Our

[21] The UBPR codes for total loans, real estate loans, C&I loans, and consumer loans are UBPRSE019, UBPRSE397, UBPRSE408, and UBPRSE410, respectively. Since "YTD net losses" 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 losses in the current quarter by the value of the YTD net losses in the last quarter.

Table 9
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 mean, median, and standard deviation of the financial ratios of interest. In the right 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 0.01, which is an almost 50% variation in the mean value of δ, which is 0.02. As our real data covers 45 quarters, we set each of our 5000 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

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

results in Table 10 show that the simulated moments are not sensitive to the exact values of the parameters used. Only the ratio of government bonds to real estate loans, with a 7% drop, appears sensitive to these changes. However, compared to the baseline simulation, this is still within the reasonable domain compared to real data. Other ratios only slightly change.[22]

To this point, we set up our model, derived its static implications, calibrated it to match the data, and demonstrated that these calibrations are not particularly sensitive to any of the parameters in our model. To observe how our model can explain and justify banks' dynamic asset adjustment behavior, we simulate the effect of a natural disaster in the next section.

6. Simulation of a disaster

In this part, we simulate the effect of a natural disaster that is assumed to destroy production capital and by Proposition 1 stimulates the 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 Models 1 and 2, we simulate a 1% increase in the capital depreciation rate. We use a 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, a 1% change can proxy the large shock induced by a rare disaster as specified 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 in Fig. 3, the capital level drops after a disaster. Firms' marginal productivity of capital increases and they need more investment to restore 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%. The bank also boosts its capital adequacy by more than 0.5%. In brief, as the bank extends new credit, our model implies a positive role for commercial banks in supporting economic recovery. But, of course, a natural disaster is not only a positive shock to firms' depreciation rates. It also (negatively) affects their ability to service outstanding debt and thereby affects their ability and willingness to issue new loans.

In a more realistic scenario, we assume the depreciation rate and default rate to be correlated. That is, a disaster destroys firm capital, interrupts production, and leads to delayed loan payments or even a default. If we assume that a 1% increase in the depreciation rate is associated with a 0.5% increase in the default rate, then, as indicated

[22] Since in Model 2, cost parameters η and ψ are vectors, we can change values for each individual element rather than uniformly increase or decrease values by 10%. We did try 10% deviations for each individual element and the results remain robust.

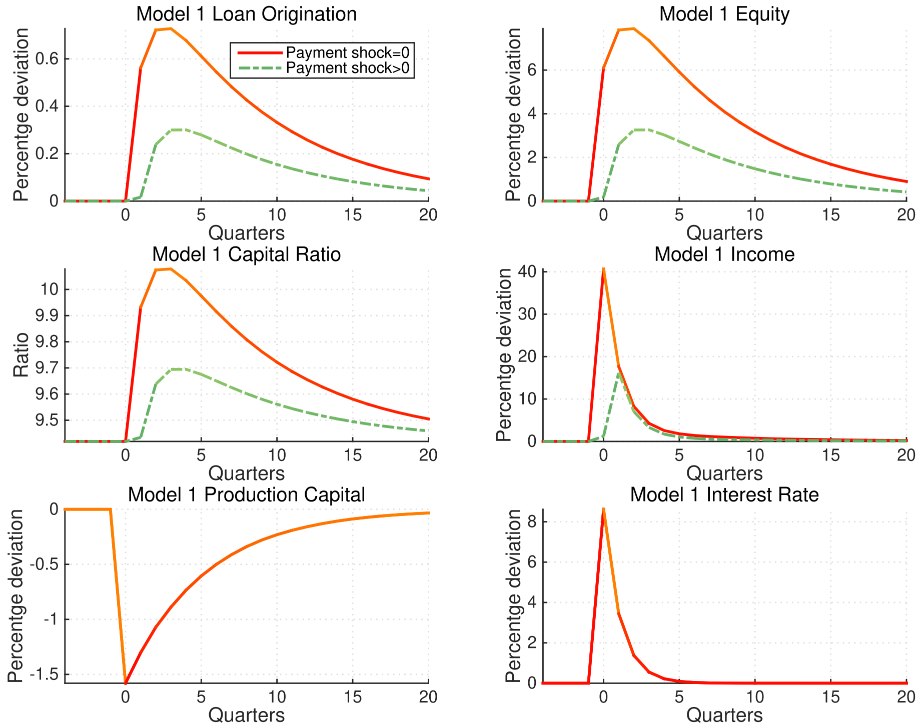

Fig. 3. Effects of a 1% Increase in the Capital Depreciation Rate on Loan Origination, Equity, the Capital Ratio (or Equity Ratio), and Income (Model 1). This figure shows the percentage deviation in loans, equity, income, firm capital, and the interest rate from their steady states and the change in the capital ratio if the capital depreciation rate δ increases by 1% after a disaster based on Model 1. The green lines represent the case in which the depreciation rate and default rate ξ are correlated; we assume that a 1% increase in the depreciation rate is associated with a 0.5% increase in the default rate. The previous five periods (i.e., -5 to -1) are interpolated as peaceful periods to improve the readability of the figure. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

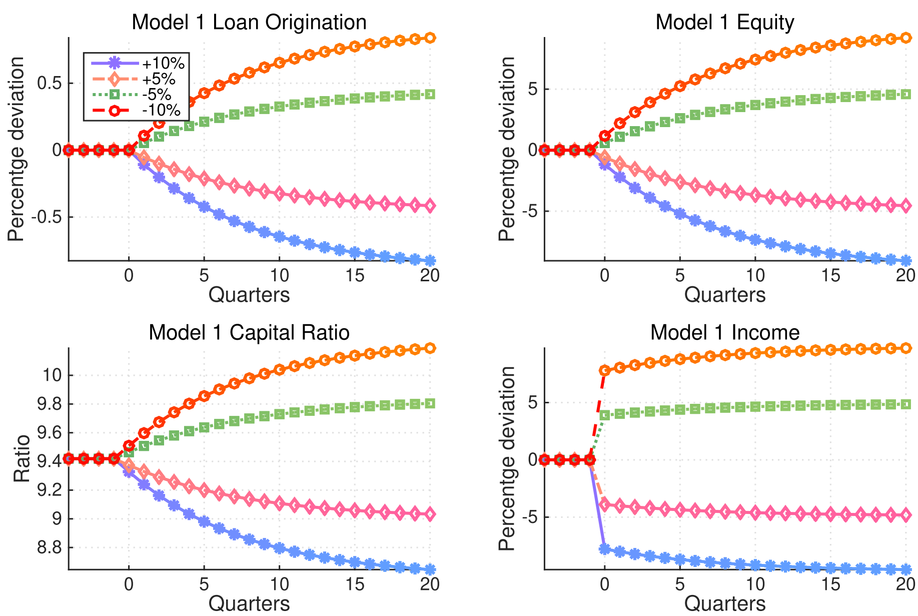

Fig. 4. Effects of a 1% Increase in the Capital Depreciation Rate on Bank Assets, Equity, Capital Ratio, and Income (Model 2). This figure shows the percentage of deviation in bank assets and income from their steady states if the capital depreciation rate δ increases by 1% after a disaster based on Model 2. The abbreviations RS, CI, and CS mean real estate loans, commercial and industrial loans, and consumer loans, respectively. The previous five periods (i.e., -5 to -1) are interpolated as peaceful periods to improve the readability of the figure.

by the green curves, banks will generate fewer new loans and all other variables will increase to a lower amount than in the previous case.

Fig. 4 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 in Model 1. The difference is that when we consider multiple assets, we can observe that the bank increases the origination of all types of loans as the interest rate increases, but, at the same time, it decreases its holdings of government bonds. Specifically, our model implies a roughly 4% increase in every type of loan and a 60% decrease in GS. Such a reallocation aligns well with our empirical findings. Our model consistently predicts increases in real estate and consumer lending and decreases in GS.

One concern is about the magnitude of the change in government bonds. The simulation implies quite a large (60%) drop, while the empirical findings reveal the drop to be around 13%. As we have stated, in this study, we highlight banks' use of an internal asset diversification strategy in response to disasters. Banks, of course, can have many other solutions for enduring disasters. In previous research, Cortés and Strahan (2017) demonstrated that banks adjust lending between affected and unaffected regions. If banks use many strategies to cope with disasters, then the drop in government bond holdings will be less. Additionally, in the data, the responses of other banks and the central bank may play a role in maintaining funding for banks in affected counties. Nevertheless, the gap to be explained here remains large and is likely to be the result of the fact that we allow banks no other way to accommodate for the shock of a natural disaster other than through asset reallocation.

We conclude that with a dynamic multiple-asset credit rationing model, we can explain why and how banks adjust their asset structure

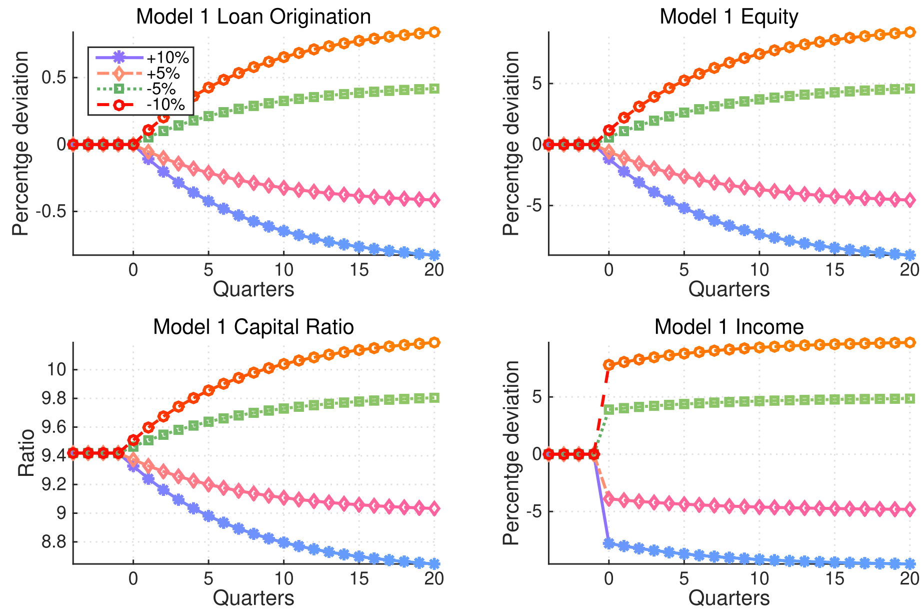

Fig. 5. Effects of Different Permanent Shocks on Disaster Probability. In this figure, we assume four different scenarios regarding the change in disaster probability. We assume permanent changes in quarterly disaster probability to be +10%, +5%, −5%, and −10%, respectively. We have scenarios of increased probability because climate change can increase the chance of a natural disaster occurring. We also show scenarios of decreased probability to compare them to the implications of climate change.

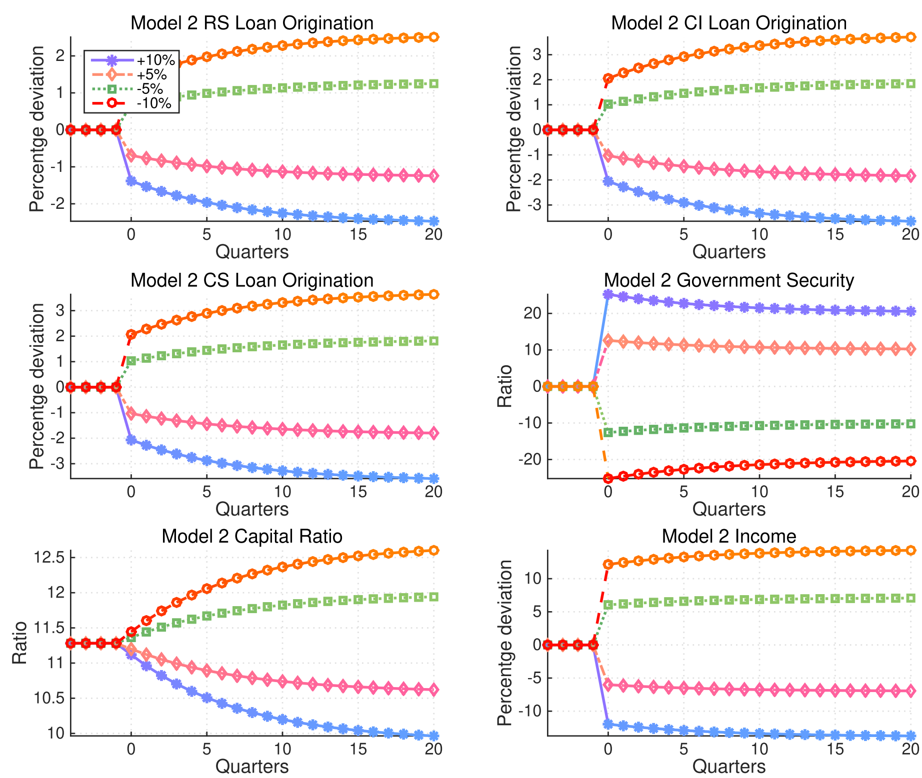

Fig. 6. Effects of Different Permanent Shocks on Disaster Probability. In this figure, we assume four different scenarios regarding the change in disaster probability. We assume the permanent changes in the quarterly disaster probability to be +10%, +5%, −5%, and −10%, respectively. We have scenarios of increased probability because climate change can increase the chance of a natural disaster occurring. We also show scenarios of decreased probability to compare them to the implications of climate change.

in response to natural disasters. By strategically (re)allocating assets, banks not only meet the increased loan demand of the local community, but also guarantee a stable income and shareholder value for themselves. In the next section, we go a step further by examining the impact of climate change on banks' asset structure.

7. Does climate change affect banks' asset structure?

Thus far, we have explored the impact of a disaster, given the setup of our model, as calibrated to the data. In the final part of our analysis, we examine what happens if the probability of a disaster occurring changes as a result of climate change. As has been predicted by the Intergovernmental Panel on Climate Change, global warming can increase the chance of a natural disaster occurring, especially floods and hurricanes, which account for a large portion of the disaster sample in our empirical analysis (Pachauri et al., 2014). Therefore, we present four scenarios of permanent changes in disaster probability (i.e., +10%, +5%, −5%, and −10%).[23]

As shown in Fig. 5, consistent with Proposition 1 in the static analysis, Model 1 implies that an increase in disaster probability leads to decreased loan origination, income, and equity. This is because a higher disaster probability means a higher expected default rate and

[23] We included the negative shocks to verify that our model is symmetrical in its response to the change in perceived natural disaster probability.

lower income and shareholder value. As a result, banks generate less credit. Since equity decreases more than loans, the capital ratio also decreases. Therefore, our model implies that climate change not only reduces banks' ability to issue credit, but also affects banks' stability since they maintain less capital.

As for Model 2, consistent with Proposition 1, Fig. 6 shows that a higher disaster probability leads to a lower level of all types of loans. However, in line with Proposition 2, banks increase their holdings of government bonds because they have a zero default rate; that is, they are independent of disaster risk and are therefore a safer asset than loans. Similar to the predictions of Model 1, in Model 2, banks' income, equity, and capital ratio also decrease in response to the climate change-induced increased probability of disaster.

To sum up, by assuming different changes in disaster probability due to climate change, our model shows that profit-maximizing banks will increase their holdings of GS and reduce loans to firms and households. This is detrimental to their income and, ultimately, to their reserves and equity ratios. Climate change thus hinders banks' capacity to issue credit to productive investments and reduces banks' capital adequacy, reducing investment and negatively affecting financial stability.

8. Conclusion

This paper examined how banks strategically reallocate their assets when a natural disaster stimulates the demand for loans, as identified in the previous literature. In the empirical analysis, we discovered that natural disasters affect banks' asset structure (i.e., banks extend loans and sell government bonds to finance the increased credit demand). The changes are both statistically and economically significant.

In the theoretical section, we developed a multiple-asset dynamic credit allocation model to explain the empirical findings. Our model includes both supply side and demand side aspects and illustrates the response of profit-maximizing banks to natural disasters and to changing underlying risks that can be linked to climate change.

The model captures bank asset allocation behavior found in the empirical analysis and has important implications for the ongoing debate regarding the economic impact of climate change. Our simulations demonstrate that a higher risk of natural disaster will erode the ability and willingness of banks to provide credit to local firms. In anticipation of more frequent and serious weather-related disasters, banks will show a rational "flight to safety" behavior, investing more in low-yielding government bonds. Such behavior is individually rational, as banks anticipate interest rate hikes in post-disaster investment booms; however, in the long run, this will erode their capital base and financial stability in disaster-prone areas. The only upside to our climate change scenarios is that governments will be able to finance deficits more cheaply. However, we believe that both banks and society would benefit were credit allocation to remain a for-profit business and were banks not forced to retreat from their core business. Preventing climate change would, of course, be a first-best solution, but if adaptation is required, a natural disaster relief fund or loan insurance scheme could be considered.

Declaration of competing interest

We declare that there is no significant competing financial, professional, or personal interests that might have influenced the performance or presentation of the work described in this manuscript.

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Appendix. *Proof of Propositions*

Proposition 1

Since at the steady state, all variables no longer vary with time, we denote the steady-state variables using letters without temporal subscripts.

At the steady state, the motion equation of equity becomes as follows:

$$E = (1 - \nu)E + R, \tag{23}$$

which implies:

$$\begin{aligned} \nu E = R &= r(1-\overline{\xi})L - r^D D - h(L) - \overline{\xi}L \\ &= [r(1-\overline{\xi}) - \eta - \overline{\xi}]L - \frac{\psi}{2}L^2 - r^D D \\ &= \nu(L - D), \end{aligned} \tag{24}$$

where the last equation is based on the balance sheet identity $L = D + E$. Rearranging the terms, yields the quadratic equation of L as follows:

$$\frac{\psi}{2}L^2 - [(1-\overline{\xi})r - \eta - \overline{\xi} - \nu]L + (r^D - \nu)D \tag{25}$$

Solving the equation yields the following:

$$L = \frac{[(1-\overline{\xi})r - \eta - \overline{\xi} - \nu] + \sqrt{[(1-\overline{\xi})r - \eta - \overline{\xi} - \nu]^2 - 2\psi(r^D - \nu)D}}{\psi} \tag{26}$$

To know how loan levels change with interest, we take the first derivative of L with respect to r as follows:

$$\begin{aligned} \frac{\partial L}{\partial r} &= \frac{(1-\overline{\xi}) + \frac{1}{2}\frac{1}{\sqrt{[(1-\overline{\xi})r-\eta-\overline{\xi}-\nu]^2 - 2\psi(r^D-\nu)D}} 2[(1-\overline{\xi})r - \eta - \overline{\xi} - \nu](1-\overline{\xi})}{\psi} \\ &= \left(\frac{[(1-\overline{\xi})r - \eta - \overline{\xi} - \nu]}{\sqrt{[(1-\overline{\xi})r - \eta - \overline{\xi} - \nu]^2 - 2\psi(r^D - \nu)D}} + 1 \right) \frac{1-\overline{\xi}}{\psi} \\ &= \left(\frac{[(1-\overline{\xi})r - \eta - \overline{\xi} - \nu]}{\sqrt{[(1-\overline{\xi})r - \eta - \overline{\xi} - \nu]^2 - 2\psi(r^D - \nu)N(1+r^D)}} + 1 \right) \frac{1-\overline{\xi}}{\psi}. \end{aligned} \tag{27}$$

Because v in reality, it is around 15%, far bigger than r and r^D, whose average values are 7% and 2%, respectively, we have the following:

$$[(1-\overline{\xi})r-\eta-\overline{\xi}-v]^2-2\psi(r^D-v)N(1+r^D)>0 \tag{28}$$

and

$$-1<\frac{[(1-\overline{\xi})r-\eta-\overline{\xi}-v]}{\sqrt{[(1-\overline{\xi})r-\eta-\overline{\xi}-v]^2-2\psi(r^D-v)N(1+r^D)}}<0. \tag{29}$$

Therefore, $\frac{\partial L}{\partial r}>0$; so the level of total loans increases with the interest rate.

To observe how loan levels change with the non-repayment rate and disaster probability, we take the first derivative of L with respect to $\overline{\xi}$ as follows:

$$\begin{aligned}\frac{\partial L}{\partial \overline{\xi}}&=\frac{-(1-r)+\frac{1}{2}\frac{1}{\sqrt{[(1-\overline{\xi})r-\eta-\overline{\xi}-v]^2-2\psi(r^D-v)D}}2[(1-\overline{\xi})r-\eta-\overline{\xi}-v](1-r)}{\psi}\\&=\left(\frac{[(1-\overline{\xi})r-\eta-\overline{\xi}-v]}{\sqrt{[(1-\overline{\xi})r-\eta-\overline{\xi}-v]^2-2\psi(r^D-v)D}}-1\right)\frac{1-r}{\psi}.\end{aligned} \tag{30}$$

Since $r^D < v$, we have the following:

$$\frac{[(1-\overline{\xi})r-\eta-\overline{\xi}-v]}{\sqrt{[(1-\overline{\xi})r-\eta-\overline{\xi}-v]^2-2\psi(r^D-v)D}}<1 \tag{31}$$

So, $\frac{\partial L}{\partial \overline{\xi}}<0$. According to our model, $\overline{\xi}=\alpha+p\xi^*$, so $\frac{\partial \overline{\xi}}{\partial p}>0$. Finally, $\frac{\partial L}{\partial p}=\frac{\partial L}{\partial \overline{\xi}}\frac{\partial \overline{\xi}}{\partial p}<0$. Therefore, the level of total loans decreases with the non-repayment rate and disaster probability.

Proposition 2

Since at the steady state, we have $vE = R$, maximizing E is equivalent to maximizing R.

$$\begin{aligned}R&=(1-\overline{\xi}_1)r_1L_1+(1-\overline{\xi}_2)r_2L_2-r^DD-\eta_1L_1-\eta_2L_2-\frac{\psi_1}{2}L_1-\frac{\psi_2}{2}L_2-\overline{\xi}_1L_1-\overline{\xi}_2L_2\\&=\left[(1-\overline{\xi}_1)r_1L_1-\eta_1L_1-\frac{\psi_1}{2}L_1-\overline{\xi}_1L_1\right]+\left[(1-\overline{\xi}_2)r_2L_2-\eta_2L_2-\frac{\psi_2}{2}L_2-\overline{\xi}_2L_2\right]-r^DD\\&\coloneqq R_1+R_2-r^DD.\end{aligned} \tag{32}$$

To solve for L_1, we take the first derivative of R with respect to L_1 as follows:

$$\frac{\partial R}{\partial L_1}=\frac{\partial (R_1+R_2)}{\partial L_1}=\frac{\partial R_1}{\partial L_1}+\frac{\partial R_2}{\partial L_2}\frac{\partial L_2}{\partial L_1}=\frac{\partial R_1}{\partial L_1}-\frac{\partial R_2}{\partial L_2}, \tag{33}$$

where the last equation is based on the balance sheet identity $L_1 + L_2 = D + E$ and thus $\frac{\partial L_2}{\partial L_1}=-1$. Notice the following:

$$\frac{\partial R_1}{\partial L_1}=[(1-\overline{\xi}_1)r_1-\eta_1-\overline{\xi}_1]-\psi_1L_1 \tag{34}$$

and

$$\frac{\partial R_2}{\partial L_2}=[(1-\overline{\xi}_2)r_2-\eta_2-\overline{\xi}_2]-\psi_2L_2, \tag{35}$$

we plug them in to the first-order condition of L_1 and replace L_2 with $D + E - L_1$ as follows:

$$\frac{\partial R}{\partial L_1}=[(1-\overline{\xi}_1)r_1-\eta_1-\overline{\xi}_1]-\psi_1L_1-[(1-\overline{\xi}_2)r_2-\eta_2-\overline{\xi}_2]+\psi_2(D+E-L_1)=0. \tag{36}$$

Solving this equation, we have the following:

$$L_1=\frac{[(1-\overline{\xi}_1)r_1-\eta_1-\overline{\xi}_1]-[(1-\overline{\xi}_2)r_2-\eta_2-\overline{\xi}_2]+\psi_2(D+E)}{\psi_1+\psi_2}. \tag{37}$$

It is easy to see that $\frac{\partial L_1}{\partial r_1}>0$ and $\frac{\partial L_1}{\partial r_2}<0$. Therefore, when one asset has an increase in the interest rate, the bank will increase their holdings of this asset and decrease their holdings of another one. This proves Proposition 2.

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The authors regret the negligence of the order of authors during the proofreading stage and request to correct the order.

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