Floods and Loan Reallocation: New Evidence*

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Abstract

We examine the impact of severe floods on the structure of corporate funding using company-level data of small businesses and bank-level data, matched with information on municipality-level flood damage. We find that bank loans increase for firms located in a flood area but decrease for physically damaged firms, with the latter increasing their dependence on trade credit over bank loans. Using the bank-level panel data, we identify the positive impact of floods on total loans but find no relationship between floods and bank financial soundness. These findings suggest that loans and resources are reallocated from physically damaged firms to other firms located in safer places nearby, thereby benefiting from recovery-related demand with fewer competitors.

Keywords: floods, natural disasters, trade credit, bank loans, climate change

JEL Classification: G21, G32, Q54

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Highlights

- Loans, especially long-term loans, increase for firms located in flood-damaged areas but not physically damaged.
- Flood-physically damaged firms reduce bank borrowing and increase their dependence on trade credit as a temporary substitute for bank loans.
- Within flood-damaged areas, bank loans shift from damaged to undamaged firms, as the latter benefit from the demand for reconstruction and the reduced competition.

1. Introduction

Climate change risk from global warming is increasingly evident. The International Panel of Climate Change (IPCC) Sixth Assessment Report (2021) reports that the increase in average surface temperatures by about one degree Celsius over the past one hundred years has increased both extreme precipitation and drought globally, and forecasts that this trend will accelerate in the future. In reply, the Financial Stability Board (FSB), an international body created to coordinate financial regulations and supervision, has published a roadmap to address climate-related financial risks in 2021, beginning with the setting of a disclosure standard and data collection (FSB 2021).

The effects of climate change are also evident in Japan. Losses due to flood disasters have increased precipitously in recent years, especially in 2018 and 2019 (Figure 1 in section 3.4.1). In fact, the total damage to public infrastructure and the private sector increased to an unprecedented level of 1,365 and 2,102 billion Japanese yen in 2018 and 2019, respectively. In response, the Japanese government has published scientific projections based on the scenarios in the IPCC report. These show that the number of days with extremely high daily precipitation of 200 mm or more will increase by about 1.5 (2.3) times if the average temperature increases by 2 (4) degrees Celsius from the end of the 20th century to the end of the 21st century.[1]

Given the increasing threat of flood disasters, many studies have attempted to investigate the impact of floods on corporate finance. However, these are usually limited to the use of bank county-level data in the US or Germany (e.g., Cortesand Strahan, 2017; Koetter et al., 2020; Ivanov et al., 2022; Rehbein and Ongena, 2022). We are motivated

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[1] See p.15 in *The Climate Change in Japan* by Ministry of Education, Culture, Sports and Technology, and Japan Meteorological Agency.

by the availability of comprehensive data about Japanese banks and firms, both of which often attract attention during large and severe natural disasters.[2] These unique data allow us to investigate the reallocation of bank loans from physically damaged firms to other firms within a flood-affected area, and to examine the substitutability between bank loans and trade credit that results.

Our empirical study comprises two parts. The first part provides an analysis at the corporate level. For this, we employ panel data on about one hundred thousand small and medium-sized enterprises (SMEs) in Japan from 2007 to 2020. We assess the current and lagged impacts of severe flooding on SME bank loans and trade credit. We detect the deviation from the firm-specific trend associated with flooding using linear regressions after controlling for firm and industry-year fixed effects and other determinants.

To identify a severe flood, we use the Statistics of Flood Damage, compiled by the Ministry of Land, Infrastructure, Transport, and Tourism (MLIT), Japan.[3] These statistics report numerical measures of flood damage for each municipality in each calendar year. We identify the municipalities affected by severe floods, which are those in the top 10 percentile of either the number of damaged houses, the total amount of damage, or the ratio of damage to taxable income for each municipality.

Floods are often localized and rarely damage an entire municipality. We identify firms physically damaged by a flood among those located in a flood-affected municipality by using the "Loss on tangible assets" item in the income statements of each firm. This item has a nonzero value when a firm suffers loss from the resale or removal of tangible

[2] "Special Feature 2: Strengthening Measures for Severe Disasters" in 2018 White Paper on Education, Culture, Sports, Science and Technology, Ministry of Education, Culture, Sports, Science and Technology, Japan,
https://www.mext.go.jp/b_menu/hakusho/html/hpab201801/detail/1420041_00005.htm

[3] https://www.e-stat.go.jp/stat-search/files?page=1&toukei=00600590&result_page=1

assets. If a firm reports a nonzero value for this item, either in the year of a flood or the following year, the removal or resale of tangible assets is plausibly due to flood damage.[4] This item enables us to identify firms physically damaged by a flood, although it tends to underestimate the actual flood damage as SMEs often keep using old machinery beyond its statutory useful life, and for which the book value is zero.

The second part of the study consists of bank-level analyses. We calculate the ratio of SME borrowers located in a top-10-percentile flood area for each bank using the earlier corporate database. This ratio serves as a measure of each bank's exposure to a flood. We then estimate the deviation from each bank's trend given the exposure to a flood in terms of the growth of total loans and deposits, and the liquidity and nonperforming loan ratios while controlling for bank-year fixed effects and other determinants.

Our main findings are as follows. From the corporate-level analysis, we find that bank loans, in particular long-term loans, increase for firms located in a flood-damaged area but not physically damaged. On the other hand, those physically damaged firms reduce borrowing from banks. The latter firms increase their dependence on trade credit to fill in their reduced bank loans. From the bank-level analysis, we consistently document a positive impact of a flood on bank lending, but do not find any significant effect of flood exposure on bank financial soundness.

Our results indicate that banks, including small local banks, shift their loans from the firms whose collateral values are damaged by floods to firms not physically damaged in the same municipality, thus benefiting from the demand for reconstruction and reduction in competitors.[5] While Cortes and Strahan (2017) show that banks increase

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[4] We owe this idea to Uesugi et al. (2018), which uses the loss on tangibles to measure the physical damage of firms and banks from earthquakes.
[5] Koide et al. (2022) provide evidence on the negative impact of flooding on land prices.

loans to their core markets by reducing loans to noncore markets, we provide novel evidence for Japan that banks reallocate loans from physically damaged to nonphysically damaged firms.

In addition, we provide new evidence that trade credit serves as a substitute for bank loans for firms that are damaged physically by flooding.[6] Both payables and receivables increase after a flood, particularly when suppliers are physically damaged by floods. This implies the presence of a domino effect in trade credit, i.e., a stop in cash payment at a firm triggers an increase in payables throughout the supply chain network. This extends Nilsen's (2002) findings that small firms use more trade credit when banks are discouraged from lending to them because of information problems. It also reinforces evidence that trade credit substitutes for bank loans when bank loans are scarce, as found by Garcia-Appendini and Montoriol-Garriga (2013) in the context of loan contraction during the Global Financial Crisis (GFC).

Together, these findings contribute to the literature examining the strategic responses of banks to natural disasters (Koetter et al., 2020; Duqi et al., 2021; Rehbein and Ongena, 2022), including the reallocation of bank loans (Cortes and Strahan, 2017; Ivanov et al., 2022), and the substitution between bank loans and alternative financing channels, including trade credit (Nilsen, 2002; Lai et al., 2022) and venture capital (Baltas et al., 2022).

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 describes our data set. Sections 4 and 5 discuss the results of the corporate- and bank-level analyses, respectively. Section 6 concludes.

[6] Japanese SMEs primarily rely on bank loans and trade credit as their two main financing sources.

2. Literature

Several empirical studies examine the impact of floods on corporate finance using the US county-year panel data, constructed using the Spatial Hazard Events and Losses Database (SHELDUS), or German county-year panel data before and after the 2013 Elbe flood. Studies using US data consistently find that banks increase loans to firms and individuals located in flood-affected areas, while reducing loans to other areas, i.e., the bank's noncore markets (Cortes and Strahan, 2017). This reduction is more significant for under-capitalized banks (Ivanov et al., 2022).

Studies also reveal that loan rates increase more than deposit rates leading to the increase in net interest margins in flood-affected areas (Barth et al., 2019), and that banks increase the sale of liquid loans (Cortes and Strahan, 2017), or increase their dependence on brokered deposits (Barth et al., 2019), to finance recovery loans. Analyses using German data provide similar results. Banks exposed to a flood-affected area increase loans (Koetter et al., 2020) and less-capitalized banks exposed to a flood reduce their lending outside flooded areas (Rehbein and Ongena, 2022). On the other hand, Noth and Rehbein (2019) find the positive impact of floods on sales and cash holdings in flood areas.

Our analyses using Japanese data, a typical bank-dependent economy where we observe increasing flood disasters, offer supportive evidence for increased bank lending after floods, particularly by banks whose core market is exposed to flooding.[7] We also obtain several new findings. First, we find that the additional loans are directed to those

[7] Empirical studies on floods in Japan remain scarce. Recently, Yamamoto and Naka (2021) analyze the impact of floods on corporate sales and profits using corporate-level panel data. They report that the impact on sales is negative but not statistically significant, while the impact on the profit rate is negative and significant for the manufacturing sector.

firms located in a flood-affected municipality, but not physically damaged by the flooding itself, rather than firms whose tangible assets are damaged. In other words, we document a loan reallocation within a disaster-affected area from those directly damaged to those that are not. This loan reallocation process promotes the reallocation of capital and employment.

Second, we find that trade credit serves as a substitute for bank loans, especially when firms are physically damaged and in need of bank finance. This reduction of loans to physically damaged firms is consistent with the existing evidence for the damage to collateral values following public warnings of a flood or earthquake-related hazard and an actual disaster (Gu et al., 2018; Ortega and Taşpınar, 2018; Uesugi, 2018; and Koide et al., 2022).

Examining short-term liquidity management following unexpected heavy snowfalls in the northeast US in 2014 and 2015, Brown et al. (2021) concluded that firms respond to negative cashflow shocks by increasing both the drawdown and facility size of credit lines by paying higher interest rates for nine months after the disaster. We believe that our result that firms depend more on trade credit arises from differences in SME financing practices between the US and Japan in that while the former use credit lines extensively, the latter do so only rarely, and no interest is required on trade credit in Japan.

Existing studies also consider bank lending behavior after other types of natural disasters. Using a data set before and after an earthquake in Japan, Hosono et al. (2016) demonstrate that among firms located outside of earthquake-hit areas, firms reduce investment to a greater extent if their main bank is in a damaged area. Similarly, Uesugi et al. (2018) conclude that firms with damaged tangible assets reduce their borrowing from banks given the reduction in collateral values.

Finally, Lu et al. (2017) examine the increase in both payables and receivables through the supply chain network following an earthquake, and Berg and Schrader (2012) identify a significant increase in loan applications and a significant reduction in approval rates after a volcano eruption in Ecuador. They argue that this increased borrowing constraint is mitigated by the preexisting bank–firm relationship. However, while these disasters bring with them more severe damage than floods, they are not directly related to climate change and occur much less frequently.

3. Data

3.1. Identification of areas severely affected by floods

We collect flood damage information in Japan from the Statistics of Flood Damage, compiled by the MLIT.[8] These statistics provide numerical measures of flood damage at the municipality level for each calendar year. The measures include the size of inundated areas, the number of damaged houses, the amount of private sector damage, including losses to assets and agricultural products and losses from temporary shutdowns, and the amount of damage to public infrastructure.

We focus on three measures: (i) the number of damaged houses; (ii) the total amount of damage, including damage in both the private sector and to public infrastructure; and (iii) the ratio of this amount to taxable income in each municipality. The first two capture the absolute size of flood damage, whereas the latter reflects the size of damage relative to the size of each municipality. To calculate the third measure, we collect taxable income

[8] If municipalities merged during the sample period, we treat these municipalities as one municipality. The statistics report ward-level values after 2009 for government ordinance designated cities, i.e., major cities except Tokyo, despite reporting city-level values, until 2009. We aggregate these into city-level values for these cities after 2009.

data from the Nikkei NEEDS FinancialQuest.[9] Among the municipalities that report any flood damage from 2006 to 2019, we specify municipalities as areas severely affected by a flood if any of the three damage measures lie in the top 10 percentile. The percentile is calculated using the entire sample period to capture the increasing trend in the severity of floods.[10]

To match this information with the corporate financial statement data, we need to identify the month of each flood to identify the accounting period affected by the flood. For this purpose, we refer to the list of prefectures, years, and months where and when the Disaster Relief Act (DRA) was applied to a flood in the White Paper on Disaster Management 2021.[11] If a municipality, severely affected by a flood as identified in the previous step, belongs to a prefecture listed in this table, we assign the month indicated in the table as the month of the flood. We augment these data with flood month information hand-collected from newspaper articles and municipality websites for those municipalities we cannot match with the DRA table. We also construct a dummy variable indicating areas damaged by an earthquake using the DRA table.

3.2. Corporate information

We collect corporate information, including financial statements, location, and bank relationships from the Tokyo Shoko Research (TSR) Corporate Financial Database and Corporate Basic Information Database from 2007 to 2020. We also collect the list of

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[9] We observe many mergers among Japanese municipalities in the 2000s. We aggregate the values of the premerger municipalities into that of the municipality in 2021 by following the data collection rule in Nikkei NEEDS. We use municipality instead of ward-level data for large cities with wards (ordinance designated cities), apart from Tokyo, where ward-level taxable income data are not available.

[10] We also applied a top-1 and top-5 percentile criteria and obtain similar results. Results not shown, but available upon request.

[11] White paper on disaster management 2021 (Cabinet Office, Japan), Appendix (p. 26), Fig. A-12 Application of the Disaster Relief Act (Since the Great Hanshin-Awaji Earthquake) as of March 4, 2021, https://www.bousai.go.jp/en/documentation/white_paper/2021.html.

suppliers and corporate customers for each firm from the TSR Corporate Relation Database. We match the flood and earthquake information to the corporate data by the municipality where the headquarters of each firm is located. Obtaining the disaster month allows us to accurately identify the accounting year when a firm suffers from a flood or an earthquake.

3.3. Bank information

The financial data of banks, including major, regional, and cooperative banks *(shinkin*), are collected from Nikkei NEEDS FinancialQuest data. We identify lending banks for each firm from the list of the ten largest lenders in TSR Corporate Basic Information.

After matching the corporate information with the bank information and the flood information, we calculate the ratio of borrowers located in a top-10-percentile flood area for each bank and define 0.3 as the cutoff. In addition, the municipalities of bank headquarters are identified using the *Nippon Kin'yu Meikan* (Japan Finance Directory) CD-ROM, published by *Nippon Kin'yu Tsushinsha*. We construct a dummy variable, *B HQ hit by quake(t),* which equals one if the head office of a main bank is located in a municipality affected by an earthquake at time *t*, or zero otherwise.

3.4. Descriptive statistics

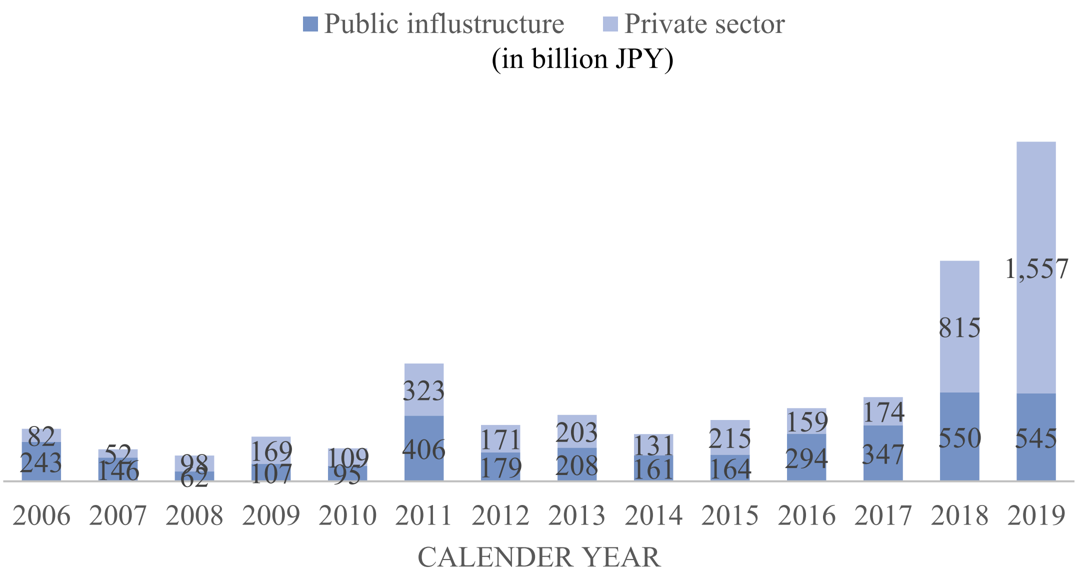
3.4.1. Flood data

Figure 1 is a time-series plot of the aggregate amount of flood damage during our data period. The figure evidences the increasing trend in flood severity and prevalence in Japan. We observe huge amounts of damage in the last two consecutive years, i.e., 2018 (1.4 trillion JPY), due to heavy rain in the western part of Japan in July, and in 2019 (2.1

trillion JPY), because of Typhoon Hagibis, which passed through almost the entirety of Japan in October. Both losses exceeded 10 billion USD.[12]

Figure 2 maps the municipalities damaged by floods. A darker color indicates more severe damage. The figure illustrates significant increases in flood severity and breadth in Panel (c) 2016–2019, partcularly in the northern part of Japan.

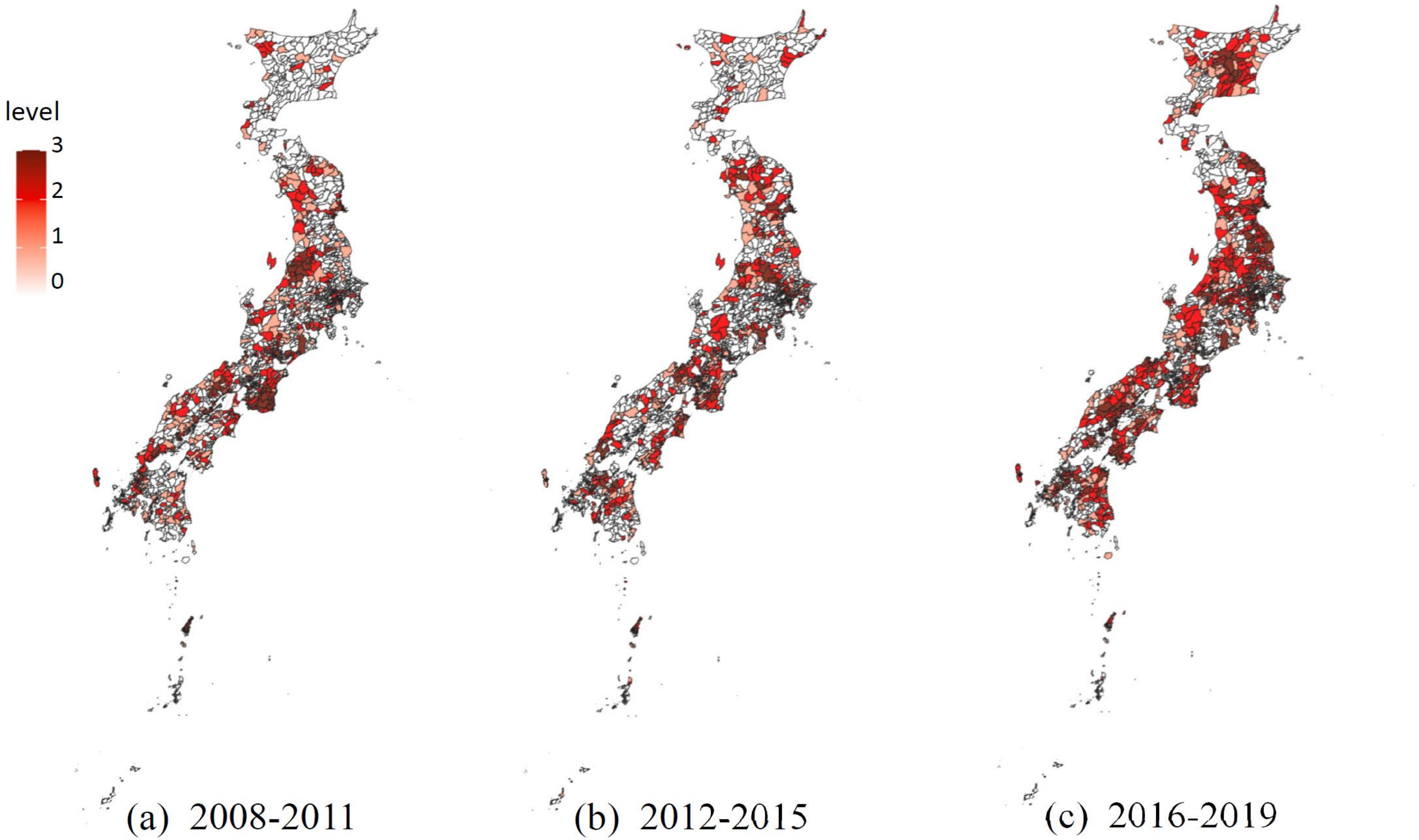
Figure 1. Aggregate damage from floods in Japan



(Source) Statistics of Flood Damage (MLIT, Japan).

[12] The estimation uses an exchange rate of 130 JPY to 1 USD.

Figure 2. Municipalities suffering from floods



(Source) Statistics of Flood Damage (MLIT, Japan).

(Note) Levels 3, 2 and 1 denote the top-1-, -5- and -10-percentile damage areas, respectively.

3.4.2. Corporate data

We focus on SMEs with less than three hundred employees, as their facilities are locally located and more likely affected by flooding. We exclude SMEs in the financial, insurance, and real estate sectors because their accounting systems or financial structures differ from other industrial companies. We also exclude outliers, as described below. We set our estimation window for our regressions from 2010 to 2020 to avoid the effect of the GFC from 2007 to 2009.

Table 1 details the number of sample firms in our data set. The total number of firms increases until 2014 owing to TSR's efforts to increase their data coverage. The number of firms in 2020 is smaller than in the other years because the database is only available until March 2020. However, we retain these observations as the flood season in Japan runs from June to October, and we can identify whether each of these observations is in a flood area. It aligns with the aggregate flood damage data in Table 1, showing a significantly high ratio of firms located in the top-10-percentile damage areas between 2018 and 2020. Of those firms located in the top-10-percentile damage areas, about 18% of firms report nonzero losses on tangible assets (final column in Table 1).

Table 1. Number of sample firms by top-10-percentile damage areas

(Note) Number of observations calculated after dropping outliers above the 99 percentile and below the 1 percentile in each year for the sales growth rate. Column 2 is the number of firms that reported nonzero losses on tangible assets among those located in top-10-percentile damage areas.

Year	(1) 10 pct damage	(2) 10 pct damage & tangible loss	(3) Others	(4) Total	(1)/(4) (%)	(2)/(1) (%)
2010	2,787	677	67,829	70,616	3.9	24.3
2011	4,138	1,010	83,254	87,392	4.7	24.4
2012	7,420	1,745	92,935	100,355	7.4	23.5
2013	4,924	948	111,091	116,015	4.2	19.3
2014	9,541	2,116	120,915	130,456	7.3	22.2
2015	5,814	1,051	130,005	135,819	4.3	18.1
2016	5,952	857	130,323	136,275	4.4	14.4
2017	6,487	1,076	129,793	136,280	4.8	16.6
2018	13,923	2,232	120,118	134,041	10.4	16.0
2019	12,933	1,957	109,997	122,930	10.5	15.1
2020	6,073	1,071	31,827	37,900	16.0	17.6
Total	79,992	14,740	1,128,087	1,208,079	6.6	18.4

One notable feature of our data set is the industrial composition. As shown in Table 2, more than half of our sample firms are in the construction sector, a far larger share than that in the Economic Census. In contrast, the retail/wholesale and service sectors are underrepresented in our sample compared with the population of SMEs. The overrepresentation of the construction sector is because of our requirement for the availability of detailed financial statements, and because construction firms tend to document accounting information carefully as it is a requirement for participating in public contracts. These features necessitate a robustness test.

Table 2. Industrial composition

(Notes) The values in the column headed "Our data set" calculated using the observations from 2010 to 2020 in our data set. Those in the column headed "Economic Census" calculated using the number of corporations in the Economic Census for Business Frame in July 2014 (Statistics Bureau of Japan).

	Our data set	Economic Census
Agriculture/forestry/fishery	0.7%	0.7%
Mining	0.2%	0.0%
Construction	58.1%	12.2%
Manufacturing	11.7%	11.2%
Information/communication	1.7%	1.2%
Transportation	2.1%	2.0%
Retail/wholesale	15.3%	24.3%
Service	10.1%	48.4%

In this study, we focus on the impact of floods on corporate financing, i.e., bank loans and trade credit. Definitions of the variables used to measure these and to control for firm or main bank characteristics are listed in Table 3(a).

Table 3. Variable definition

(a) Corporate-level data

Variables	Description	Source
damage#	Dummy variable, which equals 1 if a firm is (i) located in a municipality where there is a reported number of damaged houses, (ii) the ratio of loss amounts over taxable income, or (iii) the loss amounts are at the # (= top 1, 5, or 10) percentile or higher during the accounting period, or zero otherwise.	Flood information: Flood Disaster Statistics (Ministry of Land, Infrastructure, Transport, and Tourism, MLIT), Corporate location: TSR, Month of flood: White Paper on Disaster Management 2021 (Cabinet Office, Japan)

damage_loss#	Dummy variable, which equals 1 if a firm is (1) (i) located in a municipality where there is a reported number of damaged houses, (ii) the ratio of loss amounts over taxable income, or (iii) the loss amounts are at the # (= top 1, 5, or 10) percentile or higher, and (2) the firm reports a loss on their tangible assets, during the accounting period, or zero otherwise.	Flood information: Flood Disaster Statistics (MLIT), Corporate location: TSR, Month of flood: White Paper on Disaster Management 2021 (Cabinet Office)
hit_quake	Dummy variable, which equals 1 if a firm is located in a municipality where the Disaster Relief Act is applied for an earthquake, or zero otherwise.	White Paper on Disaster Management 2021 (Cabinet Office, Japan), Corporate location: TSR.
loan/asset	Loan(*t*)/asset(*t*–1).	TSR (Corporate financial data)
Δloan/asset	(Loan(*t*) – total loan(*t*–1))/asset(*t*–1).	TSR (Corporate financial data)
Δlong-term loan/asset	(Long-term loan(*t*) – long-term loan(*t*–1))/asset(*t*–1).	TSR (Corporate financial data)
short-term loan/asset	Short-term loan(*t*)/asset(*t*–1).	TSR (Corporate financial data)
trade credit/asset	(Payable(*t*)–receivable(t))/asset(t–1).	TSR (Corporate financial data)
payable/asset	Payable(*t*)/asset(*t*–1).	TSR (Corporate financial data)
receivable/asset	Receivable(*t*)/asset(*t*–1).	TSR (Corporate financial data)
Δtrade credit/asset	(Payable(*t*)–receivable(*t*)–payable(*t*–1)+receivable(*t*–1))/asset(*t*–1).	TSR (Corporate financial data)
Δpayable/asset	(Payable(*t*)–payable(*t*–1)/asset(*t*–1)).	TSR (Corporate financial data)
Δreceivable/asset	(Receivable(*t*)–receivable(*t*–1))/asset(*t*–1).	TSR (Corporate financial data)
sales/asset	sales(*t*)/asset(*t*–1).	TSR (Corporate financial data)
Δsales/asset	(sales(*t*)–sales(*t*–1))/asset(*t*–1).	TSR (Corporate financial data)
sales growth rate	(sales(*t*)–sales(*t*–1))/sales(*t*–1).	TSR (Corporate financial data)
cash hold	cash(*t*)/(asset(*t*)–cash(*t*)), where cash includes cash equivalent.	TSR (Corporate financial data)
Δcash hold	Change in cash(*t*)/(asset(*t*)–cash(*t*)) from the previous year, where cash includes cash equivalent.	TSR (Corporate financial data)

special income/asset	Special income (t)/asset(t–1)*100 (%). The numerator is the special income other than capital gains from assets and reversal of provisions.	TSR (Corporate financial data)
tangible loss/asset	Loss on tangible asset(t)/asset(t–1)*100 (%).	TSR (Corporate financial data)
I/K	Investment rate: (Tangible asset(t)–tangible asset(t–1)+depreciation(t))/tangible asset(t–1).	TSR (Corporate financial data)
employee	Number of employees (t).	TSR (Corporate basic information)
Δemployee	Change in the number of employees from the previous year.	TSR (Corporate basic information)
liability/asset	liability(t)/asset(t).	TSR (Corporate financial data)
credit score	Credit score (worst 0 – best 100), assigned by TSR.	TSR (Corporate basic information)
cash flow/tangible asset	(Operating profit(t) + depreciation(t))/tangible assets(t–1).	TSR (Corporate financial data)
cash flow/#employees	(Operating profit(t) + depreciation(t))/#employees(t–1).	TSR (Corporate financial data and basic information)
ec_tangible	(sales(t)–tangible asset(t))/tangible asset(t).	TSR (Corporate financial data)
ec_employee	(sales(t)–#employees(t))/#employees(t).	TSR (Corporate basic information)
MB exposure10	Exposure to a flood with top-10-percentile damage (damage1 = 1) of a main bank. Exposure is the ratio of borrowers located in a municipality with 10-percentile flood damage among all borrowers identified by TSR. Main bank is the first one in the list of lenders.	Flood Disaster Statistics (MLIT), TSR, White Paper on Disaster Management 2021 (Cabinet Office)
MB exposure_quake	Exposure to an earthquake (hit_quake = 1) of a main bank. Exposure is the ratio of borrowers located in a municipality	Earthquake information: White Paper on Disaster Management

	hit by an earthquake among all borrowers identified by TSR. Main bank is the first one in the list of lenders.	2021 (Cabinet Office), Corporate location and main bank: TSR
MB HQ hit by quake	Dummy variable, which equals 1 if the head office of a main bank is located in a municipality hit by an earthquake, zero otherwise.	Main bank: TSR, Earthquake information: White Paper on Disaster Management 2021 (Cabinet Office)
MB HQ hit by 10pc flood	Dummy variable, which equals 1 if the head office of a main bank is located in a municipality hit by a 10-percentile flood disaster (damage1 = 1), zero otherwise.	Flood Disaster Statistics (MLIT), TSR, White Paper on Disaster Management 2021 (Cabinet Office)
MB liquidity ratio	Liquidity ratio of the main bank.	Nikkei NEEDS FinancialQuest
MB leverage ratio	Leverage ratio (net asset/total asset) of the main bank.	Nikkei NEEDS FinancialQuest
government bank	Dummy variable, which equals 1 if a government-controlled bank (Development Bank of Japan, Japan Finance Corporation, Shoko Chukin Bank) has a loan outstanding to the firm in the current year, zero otherwise.	TSR (Corporate basic information)
damaged customer ratios (#%)	Ratio of corporate customers who are located in a municipality hit by a flood with # (= top 1, 5, or 10) percentile damage (damage# =1).	TSR (Corporate Relation Data, Corporate Basic Information), Flood Disaster Statistics (MILT).
damaged supplier ratio (#%)	Ratio of suppliers who are located in a municipality hit by a flood with # (= top 1, 5, or 10) percentile damage (damage # = 1).	TSR (Corporate Relation Data, Corporate Basic Information), Flood Disaster Statistics (MILT)

(b) Bank-level data

Variables	Description	Source
ln loan	Natural logarithm of total loans (mil. JPY).	Nikkei NEEDS FinancialQuest
Δln loan	Annual increase in *ln_loan* from the previous year (mil. JPY).	Same as above
ln deposit	Natural logarithm of total deposits including certificate of deposits (mil. JPY).	Same as above
Δln deposit	Annual increase in *ln_deposit* from the previous year (mil. JPY).	Same as above
liquidity ratio	Ratio of liquid assets over total assets (%). Liquid assets are the sum of cash and due from banks, call loans, receivables under a resale agreement, receivables under securities borrowing transactions, bills bought, money held in trust, and securities on the asset side (English translation by JBA).	Same as above
Δliquidity ratio	Change in liquidity ratio from the previous year.	Same as above
NPL ratio	Nonperforming loan ratio, defined by (risk-monitored loans)/(total assets) (%).	Same as above
ΔNPL ratio	Change in the NPL ratio from the previous year.	Same as above
ROA	Ordinary profit/total assets (%).	Same as above
leverage ratio	Equity capital/total assets (%).	Same as above
B_flood_exp	Dummy indicator which equals one if the ratio of SME borrowers of the main bank located in a top-10-percentile flood area is greater than a specific threshold, i.e., 0.3, or zero otherwise.	Flood Disaster Statistics (MLIT), TSR, White Paper on Disaster Management 2021 (Cabinet Office)
B_quake_exp	Dummy indicator which equals one if the ratio of SME borrowers of the main bank located in a top-10-percentile earthquake area is greater than a specific threshold, i.e., 0.3, or zero otherwise.	TSR, White Paper on Disaster Management 2021
B HQ hit by 10pc flood	Dummy indicating the headquarter of the main bank is in a municipality affected by a top-10-percentile flood.	Flood Disaster Statistics (MLIT), TSR, White Paper

		on Disaster Management 2021 (Cabinet Office)
B HQ hit by quake	Dummy variable which equals one if the main bank headquarters is in a municipality affected by an earthquake designated by the Disaster Relief Act.	TSR, White Paper on Disaster Management 2021

To avoid outliers in financial variables, we drop those below the 1 percentile and above the 99 percentile each year from our analysis.[13] The descriptive statistics after dropping these outliers are in Table 4(a).

[13] We drop outliers with respect to the following variables: *Δloan/asset*, *Δlong-term loan/asset*, *short-term loan/asset*, *payable/asset*, *receivable/asset*, *sales/asset*, *Δsales/asset*, *cash hold*, and *liability/asset*.

Table 4. Descriptive statistics

(a) Corporate-level data

(Note) Statistics are calculated from the sample from 2010 to 2020 after dropping outliers.

Variables	N	Mean	SD	Min	p1	p50	p99	Max
Δloan/asset	1,208,079	0.101	0.210	–0.377	–0.187	0.018	0.938	2.397
Δlong-term loan/asset	1,208,079	0.000	0.100	–0.511	–0.237	0.000	0.405	0.826
short-term loan/asset	1,208,079	0.101	0.188	0.000	0.000	0.006	0.912	2.209
trade credit/asset	1,208,079	–0.071	0.160	–1.140	–0.570	–0.051	0.325	0.994
payable/asset	1,208,079	0.140	0.154	0.000	0.000	0.090	0.684	1.023
receivable/asset	1,208,079	0.211	0.180	0.000	0.000	0.172	0.790	1.144
sales growth rate	1,208,079	0.047	0.342	–0.929	–0.551	0.008	1.179	17.504
Δsales/asset	1,208,079	0.028	0.487	–2.966	–1.437	0.010	1.629	3.913
cash hold	1,208,079	0.551	0.822	0.000	0.000	0.286	4.234	9.783
special income/asset	1,208,079	0.409	3.998	–4.080	0.000	0.000	8.618	1764.599
tangible loss/asset	1,208,079	0.036	0.159	0.000	0.000	0.000	1.000	1.000
tangible loss	1,208,079	0.203	0.402	0.000	0.000	0.000	1.000	1.000
liability/asset	1,208,079	0.679	0.477	0.000	0.008	0.646	2.533	6.703
credit score	1,207,810	50.642	6.544	8	37	50	67	86
MB exposure10	1,121,237	0.055	0.098	0.000	0.000	0.016	0.489	0.901
MB exposure_quake	1,121,237	0.035	0.110	0.000	0.000	0.000	0.580	0.988
MB in quake	1,119,020	0.025	0.156	0.000	0.000	0.000	1.000	1.000

MB in 10pc flood	1,119,020	0.097	0.296	0.000	0.000	0.000	1.000	1.000
MB liquidity ratio	1,157,673	41.313	13.763	5.187	20.761	39.923	97.025	97.854
MB leverage ratio	1,157,673	5.336	1.390	1.104	2.792	5.160	9.718	24.836
government bank	1,208,079	0.189	0.392	0.000	0.000	0.000	1.000	1.000
Ratio of damaged customers (10%)	1,157,009	0.017	0.085	0.000	0.000	0.000	0.429	1.000
Ratio of damaged suppliers (10%)	1,157,009	0.017	0.084	0.000	0.000	0.000	0.500	1.000

(b) Bank-level data

Variables	N	Mean	SD	Min	p1	p50	p99	Max
ln_loan	4062	12.640	1.549	9.768	10.030	12.350	16.75	18.3
Δln_loan	4062	0.012	0.036	–0.183	–0.078	0.013	0.106	0.586
ln_deposit	4062	13.260	1.396	10.510	10.990	13.050	17.08	18.91
Δln_deposit	4062	0.021	0.030	–0.256	–0.041	0.018	0.118	0.565
liquid ratio	4062	47.200	12.830	8.844	20.360	48.670	76.17	90.12
Δliquid ratio	4062	0.555	1.947	–19.870	–4.387	0.517	5.842	17.02
NPL ratio	4059	4.985	2.941	0.057	0.788	4.399	14.54	23.19
ΔNPL ratio	4058	–0.199	0.841	–7.963	–2.245	–0.210	2.299	11.18
ROA	4062	0.247	0.255	–3.330	–0.630	0.235	0.813	4.24
leverage ratio	4062	5.648	2.040	1.104	2.403	5.263	11.81	24.43
exposure10	4062	0.058	0.127	0.000	0.000	0.003	0.634	0.901
B exposure_quake	4062	0.030	0.116	0.000	0.000	0.000	0.669	0.988
B HQ hit by quake	4062	0.024	0.153	0.000	0.000	0.000	1.000	1.000

3.4.3. Bank data

Table 4(b) lists descriptive statistics for the banks in our data set. The definition of each variable is listed in Table 3(b). We do not drop any outliers.[14] The asset size of banks ranges from 20 billion JPY (about 154 million USD, 1 USD = 130 JPY) to 89 trillion JPY (about 685 million USD). Most SMEs in our corporate data set use regional banks (ranging from 200 billion JPY to 18 trillion JPY of total asset) and cooperative banks (ranging from 40 billion JPY to 5.6 trillion JPY of total asset) as their main bank. The liquidity ratios range from 9% to 90%. Some small cooperative banks show extremely high liquidity because they specialize in security investments. The nonperforming loan (NPL) ratio ranges from 0.1% to 23%. Leverage ratio (capital in B/S over total assets) varies between 1% and 24%. Most extreme values are associated with small cooperative banks. The headquarters of 2.5% of all banks were in a municipality hit by a severe earthquake.

3.5. Corporate performance in flood areas

To describe the impact of floods on corporate performance, we regress the sales growth rate on the leads and lags of *damage10*, the dummy indicating that a firm is in a top-10-percentile flood area with firm- and industry-year fixed effects (Column 1, Table 5).[15] The estimated coefficients indicate that sales increase in the year of a flood and the following year. This suggests the role of significant reconstruction demand, possibly stimulated by public expenditures used for the recovery of damaged infrastructure.

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[14] While we remove outliers from our corporate data set given the poor data quality of some SMEs, we can retain all observations in our banking data set. In general, banking data exhibit superior quality compared with SME data given the stringent regulations governing the banking sector and the larger size of banks compared with SMEs. However, our results are still robust even after removing any outliers.

[15] We use the medium classification in the Japan Standard Industrial Classification (JSIC), which is mostly equivalent to the 2-digit classification in the U.S.

To see the effect of the overrepresentation of the construction sector in our data set, we run the same regressions for each sector with firm and year fixed effects. The result in Table 6 shows that sales tend to increase after a flood in each sector in the construction, manufacturing, and service sectors. To detect physical damage by floods, we regress the loss on tangible assets, which is reported in the income statement, on the leads and lags of *damage10*. The result in Column 2 of Table 5 shows that firms tend to report losses on tangible assets in the year following a flood.[16]

To identify the possible impact of government subsidies or insurance, we also regress *special income/asset* on the leads and lags of *damage10* (Column 3, Table 5). None of the coefficients are statistically significant at any conventional levels.[17] For all three models in Table 5, we include *damage10(t+1)* to assess the validity of the parallel trend assumption. The insignificant coefficient on *damage10(t+1)* in all models confirms that the parallel trend assumption holds.

Table 5. Sales, special income, and losses on tangible assets

(Notes) Estimated coefficients shown. Dependent variable indicated at top of each column. Control variables include the leads and lags of *hit_quake.* Two-way (firm and year*industry) clustered standard errors in parentheses. Industry classification based on JSIC 2 digits. Constant term included in all models but not shown. *** p<0.01, ** p<0.05, * p<0.1 (two-sided).

	(1)	(2)	(3)
Variables	sales growth rate	tangible loss/asset	special income/asset
damage10(t+1)	–0.0012	–0.0011	0.0404
	(0.0026)	(0.0007)	(0.0372)

[16] We identify a similar pattern for earthquakes.
[17] The insignificant coefficients of flood on *special income/asset* suggest that government subsidies or insurance do not exhibit an observable increase after floods. This does not inherently imply the absence of subsidies from the Japanese government after floods. Unlike earthquakes where the central government often provides direct support to firms, government flood-related subsidies take an indirect route to firms through local government.

damage10(t)	0.0084***	0.0004	0.0042
	(0.0030)	(0.0009)	(0.0177)
damage10(t–1)	0.0070**	0.0014*	–0.0145
	(0.0030)	(0.0007)	(0.0150)
damage10(t–2)	–0.0031	0.0003	0.0291
	(0.0030)	(0.0009)	(0.0441)
N	902,948	902,948	902,948
Control variables	Yes	Yes	Yes
Adj. R-sq.	–0.0545	0.1438	0.1265
*Year*Industry FE*	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

Table 6. Sales growth by industry

(Notes) Estimated coefficients shown. Dependent variable is sales growth rate. Control variables include the leads and lags of *hit_quake.* Two-way (firm and year) clustered standard errors in parentheses. Constant term included in all models but not shown. *** p<0.01, ** p<0.05, * p<0.1 (two-sided).

	(1)	(2)	(3)	(4)
Subsample	Construction	Manufacturing	Wholesale/retail	Services
damage10(t+1)	–0.0025	0.0085	–0.0005	0.0003
	(0.0044)	(0.0055)	(0.0031)	(0.0023)
damage10(t)	0.0098*	0.0078*	0.0068	0.0086***
	(0.0051)	(0.0036)	(0.0057)	(0.0020)
damage10(t–1)	0.0114**	–0.0019	–0.0029	0.0012
	(0.0043)	(0.0035)	(0.0077)	(0.0025)
damage10(t–2)	–0.0064	0.0016	0.0142**	–0.0066**
	(0.0049)	(0.0074)	(0.0056)	(0.0024)
N	520,039	110,641	143,051	85,460
Control variables	Yes	Yes	Yes	Yes
Adj. R-sq.	–0.0766	–0.0128	0.0161	0.0242
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

4. Corporate-level analysis

4.1. Estimation model

To assess the impact of floods on corporate funding structure, we estimate their deviations from each firm-specific trend given a flood using the following linear regression.

$$y_{it} = \beta_0 + \beta_1 damage10_{it} + \beta_2 damage10_{it-1} + \beta_3 damage10_{it-2} + \beta_4' X_{it} + \eta_{st} + \mu_i + \epsilon_{it}, \quad (1)$$

where i is the index of firms, t is year, y_{it} is a measure of corporate funding, $damage10_{it}$ is a dummy variable indicating firm i is located in a top-10-percentile flood area in year t, X_{it} is the vector of control variables and β_4 the vector of their coefficients, η_{st} is the industry*year fixed effect, μ_i is the firm fixed effect, and ϵ_{it} is the error term. We cluster standard errors at the firm and sector-year levels.

The set of control variables X_{it} consists of the following three components: (i) the effect of earthquakes; (ii) firm characteristics; and (ii) main bank characteristics. The effect of earthquakes is captured by the current and lagged dummy variables, *hit_quake*, indicating a firm is in an area hit by an earthquake designated by DRA. The firm characteristics include indicators of credit quality, including the leverage and credit score assigned by TSR, and the growth potential measured by the increase in sales divided by total assets in the previous year (*Δsales/asset*).

We assume the first bank in the list of lending banks in the TSR database, which lists banks in order of lending amount, as the primary main bank for each firm. We control for exposure to a flood or an earthquake with *MB exposure10* (the ratio of SME borrowers of the main bank located in a top-10-percentile flood area), *MB exposure quake* (the ratio of SME borrowers of the main bank located in an area affected by an earthquake), *MB in quake* (a dummy variable indicating that the headquarters of the main bank is located in a municipality affected by an earthquake), and *MB in 10pc flood* (a dummy variable indicating the headquarters of the main bank is in a municipality hit by a top-10-percentile flood). We also control for the financial characteristics of main banks using *MB liquidity ratio* and *MB leverage ratio* following existing studies in the area (e.g., Thakor, 1996; Kashyap and Stein, 2000).

4.2. Bank loans

4.2.1. Baseline

Table 7 details the results of the baseline regressions for corporate funding structure following a flood.[18] As shown, bank loans increase in the year of a flood (Column 1) and this is mostly driven by long-term loans (Column 2), whereas short-term loans tend to decrease after a flood (Column 3).[19]

As for the control variables, the coefficients of *hit_quake*, the indicator of an earthquake, exhibit a similar but stronger pattern than that of a flood. Firms with high credit scores and low leverage tend to use long-term loans, while those with low credit scores and high leverage tend to use short-term loans. Firms with growing sales reduce their dependence on short-term loans but increase their dependence on long-term loans. Among the control variables regarding main bank (MB) characteristics, both *MB liquidity ratio* and *MB leverage ratio* have a negative and statistically significant coefficient (except for *MB liquidity ratio* being statistically insignificant in Column 2). These coefficients capture some form of reverse causality, i.e., the liquidity ratio (ratio of liquid assets over total assets, including loans) and the leverage ratio (ratio of capital over total assets) tend to decline for banks that aggressively increase lending. The positive and statistically significant coefficient of *MB exposure10* in Columns 1 and 2 suggests that banks

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[18] In unreported tests, we reestimate Table 7 where year*industry and city fixed effects are used instead of year*industry and firm fixed effects. Our results remain robust and are available upon request.

[19] Long-term loan is measured by change while short-term loan is measured by level rather than change, because we would like to detect the impact on newly provided loans in each year.

with greater exposure to the flooded municipality tend to increase their lending to borrowers after floods, especially in the form of long-term loans.

Table 7. Loans after a flood: Baseline

(Notes) Estimated coefficients shown. Dependent variable indicated at top of each column. Firm and sector-year two-way clustered standard errors in parentheses. Constant term included in all models but not shown. *** p<0.01, ** p<0.05, * p<0.1 (two-sided).

	(1)	(2)	(3)
Variables	*Δloan/asset*	*Δlong-term loan/asset*	*short-term loan/asset*
damage10(t)	0.0014*	0.0015***	–0.0002
	(0.0007)	(0.0005)	(0.0005)
damage10(t–1)	–0.0010	0.0002	–0.0012**
	(0.0008)	(0.0006)	(0.0006)
damage10(t–2)	0.0001	0.0006	–0.0004
	(0.0007)	(0.0005)	(0.0005)
hit_quake(t)	0.0081***	0.0077***	0.0004
	(0.0023)	(0.0012)	(0.0016)
hit_quake(t–1)	0.0017	0.0033***	–0.0016**
	(0.0014)	(0.0013)	(0.0008)
hit_quake(t–2)	–0.0037**	–0.0004	–0.0033**
	(0.0015)	(0.0010)	(0.0014)
leverage(t–1)	0.0778***	–0.0589***	0.1366***
	(0.0050)	(0.0032)	(0.0028)
cash hold(t–1)	–0.0074***	–0.0054***	–0.0020***
	(0.0008)	(0.0006)	(0.0004)
credit score(t–1)	–0.0005***	0.0011***	–0.0016***
	(0.0002)	(0.0001)	(0.0001)
Δsales/asset(t–1)	–0.0135***	–0.0078***	–0.0057***
	(0.0009)	(0.0005)	(0.0006)
special income/asset	–0.0005***	–0.0000	–0.0004***
	(0.0001)	(0.0001)	(0.0001)
MB exposure10(t)	0.0057**	0.0042***	0.0015
	(0.0024)	(0.0016)	(0.0017)

MB exposure_quake(t)	0.0025	0.0025	–0.0000
	(0.0057)	(0.0030)	(0.0035)
MB in quake(t)	–0.0017	–0.0043***	0.0026
	(0.0037)	(0.0015)	(0.0027)
MB in 10pc flood(t)	–0.0003	–0.0009	0.0006
	(0.0008)	(0.0006)	(0.0004)
MB liquidity ratio(t)	–0.0001***	–0.0000	–0.0001***
	(0.0001)	(0.0000)	(0.0000)
MB leverage ratio(t)	–0.0020***	–0.0009***	–0.0012***
	(0.0004)	(0.0003)	(0.0003)
N	1,116,932	1,116,932	1,116,932
Adj. R-sq.	0.6237	0.0379	0.7840
Year*Industry FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

4.2.2. Physically damaged or not

Our previous results capture the average impact of floods on firms located in flood municipalities. However, the damage of a flood tends to be highly localized within a municipality. Some parts of a city are inundated, but others often remain unaffected, at least directly. To see whether the increase in loans is from those firms whose assets are physically damaged by a flood or from other firms outside a damaged area within a flooded municipality, we introduce the interaction term of $damage10$, a dummy variable to indicate a top-10-percentile flood, and $tangible\ loss$, a dummy variable that equals one if a firm reports a nonzero loss on its tangible assets. We also specify current and lagged tangible loss as control variables to control for other unobservable determinants of the loss on tangible assets.

Table 8. Loans after a flood: Physically damaged or not

(Notes) Estimated coefficients shown. Dependent variables indicated at the top of each column. Control variables include those in Table 7 and *tangible loss (t, t - 1, t - 2).* Firm and sector-year two-way clustered standard errors in parentheses. Constant term included in all models but not shown. *** p<0.01, ** p<0.05, * p<0.1 (two-sided).

	(1)	(2)	(3)
Variables	*Δloan/asset*	*Δlong-term loan/asset*	*short-term loan/asset*
damage10(t)	0.0015**	0.0014***	0.0001
	(0.0007)	(0.0005)	(0.0005)
damage10(t–1)	–0.0004	0.0008	–0.0011*
	(0.0009)	(0.0007)	(0.0006)
damage10(t–2)	0.0001	0.0007	–0.0005
	(0.0008)	(0.0006)	(0.0005)
*damage10*tangible loss(t)*	–0.0011	0.0014	–0.0025***
	(0.0013)	(0.0011)	(0.0009)
*damage10*tangible loss(t–1)*	–0.0055***	–0.0032***	–0.0023**
	(0.0015)	(0.0010)	(0.0010)
*damage10*tangible loss(t–2)*	–0.0024	–0.0018*	–0.0006
	(0.0017)	(0.0010)	(0.0011)
t-test for sum of coef. (t)	0.0003	0.0028**	–0.0024***
	(0.0014)	(0.0011)	(0.0009)
t-test for sum of coef. (t–1)	–0.0059***	–0.0024**	–0.0035***
	(0.0013)	(0.0010)	(0.0008)
t-test for sum of coef. (t–2)	–0.0022	–0.0012	–0.0011
	(0.0014)	(0.0008)	(0.0010)
Control variables	Yes	Yes	Yes
N	1,116,932	1,116,932	1,116,932
Adj. R-sq.	0.6236	0.0379	0.7839
Controls	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

Table 8 details the results of this regression analysis. The coefficients for *damage10* and its lags display the same pattern as those in Table 7. However, the interaction term of *damage10* and *tangible loss* presents a negative coefficient in the current year, the next year, and two years after a flood. The coefficient is statistically significant in the next year. This implies that while firms located in a municipality affected by a flood increase their borrowings, physically damaged firms do not. Rather, the *t*-tests for the sum of coefficients in each year (the lower part of Table 8) indicate that these firms may even reduce their borrowing from banks in the next year of a flood.[20] A potential explanation is that the damage to collateral values from a disaster has negatively affected borrowing from banks.[21]

The results thus far indicate that banks shift their lending from borrowers physically damaged to those located nearby but not physically damaged as the latter benefit from strong demand associated with reconstruction after the flood along with a smaller number of competitors.

4.2.3. Main bank located in a flood area

It is plausible that the results so far are primarily driven by firm factors, such as loan demand and credit quality, rather than by bank factors. To explore this further, we augment the above regressions with the interactions between the dummy variable indicating whether the main bank's headquarters is in a municipality affected by a top-10-percentile flood, *MB in 10pc flood*, with the flood dummies. Table 9 reports the results. The estimated coefficients for *damage10* and its interaction term with *tangible loss* display a similar pattern as those in Table 8, although the statistical significance is weaker. In fact, most of the interaction terms of *MB in 10pc flood* are not statistically significant except for the interaction term of *damage10*, *tangible loss*, and *MB in 10pc flood* in the year of a flood. The coefficients for this term is positive and statistically significant, suggesting that a bank does not decrease lending immediately for physically damaged firms located in its core market close to the vicinity of its headquarters.

[20] We identify a similar pattern for earthquakes.
[21] Uesugi et al. (2018) provide evidence that the collateral damage from the Great East Japan Earthquake in 2011 significantly reduced bank loans.

However, we do not observe this same shock mitigation behavior in later periods. On balance, we conclude that the results thus far are primarily driven by firm rather than bank factors.

Table 9. Loans after a flood: Main bank in a flood

(Notes) Estimated coefficients shown. Dependent variables indicated at the top of each column. *MB in 10pc flood* is a dummy variable indicating that the headquarters of the main bank is in a municipality affected by a top-10-percentile flood. Control variables are the same as those in Table 8. Firm and industry-year two-way clustered standard errors in parentheses. Constant term included in all models but not shown. *** p<0.01, ** p<0.05, * p<0.1 (two-sided).

Variables	(1) *Δloan/asset*	(2) *Δlong-term loan/asset*	(3) *short-term loan/asset*
damage10(t)	0.0009	0.0010*	–0.0001
	(0.0009)	(0.0006)	(0.0007)
damage10(t–1)	0.0007	0.0009	–0.0002
	(0.0011)	(0.0008)	(0.0007)
damage10(t–2)	0.0008	0.0006	0.0002
	(0.0010)	(0.0006)	(0.0007)
*damage10*tangible loss(t)*	–0.0036**	–0.0012	–0.0024**
	(0.0016)	(0.0012)	(0.0011)
*damage10*tangible loss(t–1)*	–0.0059***	–0.0030**	–0.0029***
	(0.0020)	(0.0015)	(0.0010)
*damage10*tangible loss(t–2)*	–0.0035*	–0.0018	–0.0017
	(0.0019)	(0.0012)	(0.0012)
*damage10*MB in 10pc flood(t)*	0.0012	–0.0001	0.0012
	(0.0013)	(0.0010)	(0.0010)
*damage10*MB in 10pc flood(t–1)*	–0.0023	–0.0004	–0.0019*
	(0.0015)	(0.0009)	(0.0011)
*damage10*MB in 10pc flood(t–2)*	–0.0018	–0.0001	–0.0017
	(0.0016)	(0.0010)	(0.0012)
*damage10*tangible loss*	0.0054**	0.0058***	–0.0004
**MB in 10pc flood(t)*	(0.0025)	(0.0019)	(0.0018)
*damage10*tangible loss*	0.0007	–0.0007	0.0013
**MB in 10pc flood(t–1)*	(0.0029)	(0.0020)	(0.0017)
*damage10*tangible loss*	0.0022	–0.0003	0.0025

**MB in 10pc flood(t–2)*	(0.0029)	(0.0020)	(0.0020)
Control variables	Yes	Yes	Yes
Observations	1,109,578	1,109,578	1,109,578
Adjusted R-squared	0.6242	0.0377	0.7843
Controls	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

4.3. Trade credit and cash holding after a flood

4.3.1. Baseline

Table 10 details the regression results for trade credit. We define trade credit as accounts payable minus accounts receivable, i.e., net short-term borrowing from other firms. As shown, both payables and receivables increase significantly in the year of a flood. This is because firms affected by a flood cease paying cash for goods and services, which results in an increase in payables for these firms (Column 2) and an increase in receivables for other firms (Column 3). However, these increased receivables are cashed in the next year of a flood, possibly factored by banks. The reduction in receivables could also arise from a deterioration in the creditworthiness of their customers. Only payables remain at a higher level in the year after flood, which in turn contributes to a higher level of net trade credit (Column 1).

The estimated coefficients of the control variables indicate that firms with higher leverage or credit scores depend more on trade credit. An increase in sales in the current year also increases both payables and receivables. A notable coefficient among the main bank characteristics is the leverage or capital ratio, with the estimated sign suggesting better capitalized main banks depend less on trade credit.

Table 10. Trade credit after a flood: Baseline

(Notes) Estimated coefficients shown. Dependent variables indicated at the top of each column. Constant term included in all models but not shown. Firm and industry-year two-way clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 (two-sided).

	(1)	(2)	(3)
Variables	trade credit/asset	payable/asset	receivable/asset
damage10(t)	–0.0001	0.0013***	0.0014**
	(0.0005)	(0.0005)	(0.0006)
damage10(t–1)	0.0016***	0.0004	–0.0012**
	(0.0005)	(0.0004)	(0.0005)
damage10(t–2)	0.0013***	–0.0003	–0.0016***
	(0.0004)	(0.0006)	(0.0005)
hit_quake(t)	–0.0025	0.0035**	0.0060*
	(0.0018)	(0.0016)	(0.0031)
hit_quake(t–1)	0.0026**	0.0050***	0.0024*
	(0.0013)	(0.0017)	(0.0012)
hit_quake(t–2)	0.0033***	0.0002	–0.0031***
	(0.0010)	(0.0007)	(0.0011)
leverage(t–1)	0.0106***	–0.0074***	–0.0180***
	(0.0030)	(0.0025)	(0.0016)
cash hold(t–1)	–0.0019	0.0029***	0.0049***
	(0.0014)	(0.0004)	(0.0017)
credit score(t–1)	0.0003***	–0.0008***	–0.0011***
	(0.0001)	(0.0001)	(0.0001)
Δsales/asset(t–1)	–0.0217***	0.0579***	0.0796***
	(0.0008)	(0.0017)	(0.0015)
special income/asset	0.0000	–0.0000	–0.0000
	(0.0000)	(0.0000)	(0.0000)
MB exposure10(t)	–0.0041***	–0.0021	0.0020
	(0.0015)	(0.0016)	(0.0013)
MB exposure_quake(t)	0.0034**	0.0045*	0.0011
	(0.0016)	(0.0024)	(0.0033)
MB in quake(t)	0.0007	–0.0029	–0.0036
	(0.0016)	(0.0018)	(0.0030)
MB in 10pc flood(t)	0.0002	0.0015***	0.0013**
	(0.0006)	(0.0004)	(0.0005)
MB liquidity ratio(t)	0.0001**	–0.0000	–0.0001*

	(0.0000)	(0.0000)	(0.0000)
MB leverage ratio(t)	0.0005*	–0.0005*	–0.0011**
	(0.0003)	(0.0003)	(0.0005)
N	1,116,932	1,116,932	1,116,932
Adj. R-sq.	0.6583	0.7649	0.7118
Year*Industry FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

4.3.2. Physically damaged

To observe the differences (if any) between firms physically damaged by flooding and those that are not, we include a dummy variable, *tangible loss*, which equals one if a firm reports a nonzero loss on its tangible assets, and the interaction term between this and *damage10*.

Table 11. Trade credit after a flood: Damaged and Not Damaged

(Notes) Estimated coefficients shown. Dependent variables indicated at the top of each column. Control variables include those in Table 10 and *tangible loss (t, t – 1, t – 2)*. Firm and industry-year two-way clustered standard errors in parentheses. Constant term included in all models but not shown. *** p<0.01, ** p<0.05, * p<0.1 (two-sided).

	(1)	(2)	(3)
Variables	trade credit/asset	payable/asset	receivable/asset
damage10(t)	–0.0003	0.0013**	0.0016**
	(0.0006)	(0.0006)	(0.0007)
damage10(t–1)	0.0017***	0.0005	–0.0012**
	(0.0005)	(0.0005)	(0.0006)
damage10(t–2)	0.0012**	–0.0005	–0.0018***
	(0.0005)	(0.0006)	(0.0005)
*damage10*tangible loss(t)*	0.0019*	0.0007	–0.0012
	(0.0011)	(0.0008)	(0.0010)
*damage10*tangible loss(t–1)*	–0.0001	–0.0012	–0.0010
	(0.0009)	(0.0008)	(0.0009)
*damage10*tangible loss(t–2)*	0.0008	0.0016**	0.0008

	(0.0010)	(0.0007)	(0.0010)
t-test for sum of coef. (t)	0.0016*	0.0019***	0.0004
	(0.0008)	(0.0006)	(0.0008)
t-test for sum of coef. (t–1)	0.0015*	–0.0007	–0.0022***
	(0.0007)	(0.0006)	(0.0008)
t-test for sum of coef. (t–2)	0.0019**	0.0010	–0.0009
	(0.0008)	(0.0007)	(0.0009)
N	1,116,932	1,116,932	1,116,932
Adj. R-sq.	0.6583	0.7650	0.7118
Controls	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

Table 11 details the results of the estimations. As shown, the estimated coefficients for *damage10* and its lags are the same as Table 10. A stark difference relates to the coefficient for the interaction term in the year of a flood, *damage10*tangible loss(t)*. While firms in the flood area, on average, do not adjust their trade credit balance in the year of a flood (Column 1), those that are physically damaged by flood increase their dependence on trade credit, as evidenced by the positive and statistically significant coefficient for *damage10*tangible loss(t)* in Column 1. This suggests that a physically damaged firm initiates a chain increase in trade credit, such that a supplier to a physically damaged firm is likely to increase receivables while waiting for payment by the damaged customer. The supplier in turn may need to increase its own payables while waiting for the customer's repayment.

4.3.3. Damaged suppliers and customers

To ensure these results are not driven by supply disruption, we include the share of corporate customers or suppliers located in a top-10-percentile flood area that report nonzero losses on their tangible assets into the model in Table 11. Table 12 summarizes the results of this regression. Overall, our previous results in terms of *damage10* and the interaction between *damage10* and *tangible loss* remain robust after controlling for the share of damaged supplier/customer. The damaged supplier ratio displays a positive and significant coefficient in the regressions for payables (Column 2) and receivables (Column 3). This indicates that supply disruption hampers production due to the high cost of finding alternative suppliers, leading to higher payables in firms with higher damaged supplier ratio.

Because of this disruption, it is then difficult for these supplier firms to pay in cash to their input suppliers. Other firms dependent on input from the damaged suppliers respond similarly, which could include customer firms. The increase in payables in customer firms then triggers an increase in receivables while awaiting cash from payables. In contrast, the damaged customer ratio displays a negative and significant coefficient for the regression with receivables. This implies that firms decrease their acceptance of receivables when customer credit quality is damaged by a flood. Interestingly, the coefficients for the interaction term *damage10*tangible loss* are unaffected through the introduction of the damaged customer/supplier ratio in the model specification. This suggests that physically damaged firms serve as the starting point of the chain reaction in trade credit.

Table 12. Trade credit after a flood: Damage on Customers and Suppliers

(Notes) Estimated coefficients shown. Dependent variable indicated at the top of each column. Control variables are the same as those in Table 11. Firm and industry-year two-way clustered standard errors in parentheses. Constant term included in all models but not shown. *** p<0.01, ** p<0.05, * p<0.1 (two-sided).

	(1)	(2)	(3)
Variables	trade credit/asset	payable/asset	receivable/asset
damage10(t)	–0.0002	0.0010*	0.0012
	(0.0007)	(0.0006)	(0.0008)
damage10(t–1)	0.0012**	0.0004	–0.0008
	(0.0005)	(0.0005)	(0.0005)
damage10(t–2)	0.0012**	–0.0006	–0.0018***

	(0.0005)	(0.0006)	(0.0005)
*damage10*tangible loss(t)*	0.0017*	0.0006	–0.0011
	(0.0010)	(0.0008)	(0.0010)
*damage10*tangible loss(t–1)*	–0.0001	–0.0013	–0.0012
	(0.0010)	(0.0008)	(0.0009)
*damage10*tangible loss(t–2)*	0.0007	0.0014**	0.0008
	(0.0010)	(0.0007)	(0.0010)
damaged supplier ratio(t)	0.0000	0.0041***	0.0040***
	(0.0017)	(0.0013)	(0.0013)
damaged supplier ratio(t–1)	0.0019	0.0017*	–0.0002
	(0.0014)	(0.0010)	(0.0017)
damaged supplier ratio(t–2)	0.0001	–0.0007	–0.0008
	(0.0014)	(0.0011)	(0.0016)
damaged customer ratio(t)	0.0017	0.0019	0.0003
	(0.0016)	(0.0014)	(0.0012)
damaged customer ratio(t–1)	0.0028*	–0.0006	–0.0034**
	(0.0015)	(0.0012)	(0.0016)
damaged customer ratio(t–2)	0.0009	0.0010	0.0000
	(0.0016)	(0.0013)	(0.0016)
Control variables	Yes	Yes	Yes
N	1,069,697	1,069,697	1,069,697
Adj. R-sq.	0.6597	0.7662	0.7113
Year*Industry FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

4.4. Robustness checks

We conduct a battery of additional analyses which serve as robustness checks. The results are in the appendix. First, we conduct pretrend analysis to ensure that the impact of disasters is exogenous by reestimating all our previous regressions but adding a one-year-lead dummy for floods. The results so far are robust against this modification. Second, we reestimate our baseline regression where instead of using variables to control for main bank characteristics, we employ bank-year fixed effects by adding a dummy variable that indicates borrowing from government-controlled banks. Again, our results remain robust.

Third, as the statistics in Table 2 reveal the over presence of the construction sector in our sample, we rerun our regressions with a data set excluding the construction sector. The results regarding loans are statistically significant but weaker in other sectors than in the sample with the construction sector. However, the result that physically damaged firms rely more on trade credit is stronger in the subsample excluding the construction sector than in the entire sample. Finally, we restrict our sample to include (i) firms from 2014 to avoid the macroeconomic shock arising from the Great East Japan Earthquake in March 2011, and (ii) firms with at least ten years of observations to reduce the noise from firms less frequently monitored by TSR. The results so far are robust for all subsamples, and more statistically significant than previously.

5. Bank-level analysis

In this section, we examine how exposure to floods affects bank performance, i.e., bank loans, deposits, liquidity, and nonperforming loans. We estimate the following regression equation using a sample of regional and *shinkin* banks, both being the main providers of SME loans whose branch networks are confined within a local area.[22]

$$y_{bt} = \beta_0 + \beta_1 B\_flood\_exp_{bt} + \beta_2 B\_flood\_exp_{bt-1} + \beta_3 B\_flood\_exp_{bt-2} + \beta_4' X_{bt} + \eta_t + \mu_b + \epsilon_{it}, \quad (2)$$

where *b* is the index of banks, *t* is year, and y_{bt} are bank performance measures, including changes in total loans (Δln_loan), deposits ($\Delta ln\_deposit$), levels of liquidity ratio (liquidity) and nonperforming loan ratio (*NPL ratio*). We follow Koetter et al. (2020) and define *B_flood_exp* (*B_quake_exp*) as a dummy indicator that equals one if the ratio of SME borrowers of bank i located in a top-10-percentile flood (earthquake) area is greater than a

[22] The sample of regional and *shinkin* banks includes 3,994 observations, accounting for 97.4% of all observations in our sample.

specific threshold, i.e., 0.3, or zero otherwise. X_{bt} is the vector of control variables, β_4 is the vector of their coefficients, and η_t and μ_b are year and bank fixed effects, respectively. The regression results of Equation (2) are presented in Table 13.

Table 13. Bank-level analyses

(Notes) Estimated coefficients using bank-level data shown. Dependent variable indicated at the top of each column. Bank and year two-way clustered standard errors in parentheses. Constant term included in all models but not shown. *** p<0.01, ** p<0.05, * p<0.1 (two-sided).

Variables	(1) *Δln_loan*	(2) *Δln_deposit*	(3) *liquidity ratio*	(4) *NPL ratio*
B_flood_ exp(t)	0.000	0.000	–0.174	–0.116
	(0.003)	(0.003)	(0.295)	(0.106)
B_flood_ exp (t–1)	0.007*	0.005	–0.093	–0.053
	(0.004)	(0.003)	(0.317)	(0.134)
B_flood_ exp (t–2)	0.005	–0.003	–0.594	0.066
	(0.004)	(0.002)	(0.381)	(0.127)
B_quake_exp(t)	–0.004	0.007	1.705**	0.163
	(0.006)	(0.005)	(0.605)	(0.105)
B_quake_exp(t–1)	–0.005	–0.000	1.244	–0.140
	(0.006)	(0.008)	(0.829)	(0.312)
B_quake_exp(t–2)	0.001	0.008**	1.359***	–0.127
	(0.005)	(0.003)	(0.390)	(0.235)
B HQ hit by 10pc flood (t)	–0.001	0.003	0.162	0.104
	(0.002)	(0.002)	(0.233)	(0.070)
B HQ hit by 10pc flood (t–1)	–0.003**	–0.002	0.249	0.022
	(0.001)	(0.002)	(0.215)	(0.096)
B HQ hit by 10pc flood (t–2)	–0.002	0.002	0.489*	–0.084
	(0.003)	(0.001)	(0.227)	(0.088)
B HQ hit by quake(t)	0.003	–0.004	–1.752**	0.264*
	(0.008)	(0.006)	(0.655)	(0.124)
B HQ hit by quake(t–1)	0.015*	0.026**	–0.880	0.658*
	(0.007)	(0.008)	(0.867)	(0.315)
B HQ hit by quake(t–2)	0.005	0.012	–0.241	0.683*
	(0.007)	(0.007)	(0.752)	(0.334)

ROA(t–1)	0.009**	0.002		
	(0.003)	(0.004)		
liquidity ratio(t–1)	0.001***	–0.001**		
	(0.000)	(0.000)		
leverage ratio(t–1)	0.001	0.001		
	(0.001)	(0.002)		
N	3,994	3,994	3,994	3,991
Adj. R-sq.	0.341	0.250	0.957	0.862
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

As shown in Column 1, bank exposure to floods has a positive effect on bank loans, with the coefficient of the lagged measure being statistically significant at the 10% level. This finding is consistent with the average increase in corporate borrowings first documented in Table 7. However, we do not find significant evidence concerning the association between bank exposure to earthquakes and changes in total loans, as indicated by the statistically insignificant coefficient of *B_quake_exp* and its lags. The positive coefficient of the first lag of *B HQ hit by quake*, a dummy variable indicating that a bank's headquarters is in an earthquake-hit municipality, implies that bank loan growth increases with a one-year lag after a bank's headquarter experiences an earthquake.

Consistent with the existing literature, a bank increases lending to its core market where its head office is located following a natural disaster. The coefficient of *ROA* is positive and statistically significant at the 5% level, and the coefficient of liquidity ratio is positive and significant at the 1% significance level. These results are consistent with existing evidence that banks lend more when they are more profitable and liquid. However, we do not find any significant association between the lagged measure of leverage and bank loans as suggested in the literature.

Column 2, Table 13, reports the regression results concerning changes in bank deposits. Overall, bank deposits do not change significantly in response to flood exposure. All the lags of *B_flood_exp* have statistically insignificant coefficients at any conventional level. However, bank deposits increase significantly in response to high levels of exposure to earthquakes, i.e., the coefficient of the second lagged measure, *B_quake_exp(t-2)*, is positive and statistically significant at the 5% level. This indicates the impact of the massive government subsidies for firms and households experiencing an earthquake. Column 2 also shows the negative and statistically significant effect of lagged liquidity ratio on deposit growth. In addition, the deposit growth decreases when the bank's headquarters experiences an earthquake. The evidence in Column 3 reveals that the bank's liquidity ratio is unaffected by exposure to floods. Specifically, the coefficients of *B_flood_exp* and its lags are negative, and they are all statistically insignificant at any conventional level. In Column 4, we obtain no supportive evidence for the relationship between flood exposure and banks nonperforming loans. Overall, the empirical evidence suggests that flood exposure exerts a positive impact on bank loans, but has no significant impact on other aspects of bank performance.

6. Conclusion

We examine the financial impact of severe floods in Japan during the period 2010–2020. We conduct empirical analyses at both the corporate and bank levels using comprehensive data sets of about one hundred thousand SMEs and about 380 banks in Japan. For the corporate-level analysis, on average, we obtain supporting evidence for the recovery lending channel that is well documented in the literature (e.g., Cortes and Strahan, 2017; Koetter et al., 2020). We also observe the heterogenous impact of floods on corporate policies within flood-damaged areas. Firms that are in flood areas but not physically damaged by floods increase their bank loans, especially long-term loans, whereas the opposite is found in firms physically damaged by floods.

With less reliance on bank loans, the latter tend to rely on alternative financing sources, i.e., trade credit, which mostly comes from the tightening of trade credit policy leading to a reduction in receivables. Further analysis conducted at the bank level, where we find some positive and significant impact of floods, suggests banks increase lending to disaster-affected areas. All these findings are important in that severe floods forcibly reallocate economic resources from vulnerable areas to safer areas. The forecasted increase in the frequency and magnitude of floods in Japan implies a wider range of geographical resource reallocation in the future.

References

Baltas, K., Fiordelisi, F., and Mare, D. S. (2022), "Alternative finance after natural disasters," *British Journal of Management* 33(1): 117-137.

Barth, J. R., Y. Sun, and S. Zhang, (2019), "Banks and natural disasters," Available at SSRN: https://ssrn.com/abstract=3438326 or http://dx.doi.org/10.2139/ssrn.3438326.

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

Brown, J. R., M. T. Gustafson, and I. T. Ivanov, (2021), "Weathering cash flow shocks," *Journal of Finance* 79(4): 1731-1772.

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

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

Financial Stability Board, (2021), "FSB roadmap for addressing climate-related financial risks," Available at https://www.fsb.org/2021/07/fsb-roadmap-for-addressing-climate-related-financial-risks/.

Garcia-Appendini, E., and J. Montoriol-Garriga, (2013), "Firms as liquidity providers: Evidence from the 2007-2008 financial crisis," *Journal of Financial Economics* 109(1): 272-291.

Gu, T., M. Nakagawa, M. Saito, and H. Yamaga, (2018), "Public perceptions of earthquake risk and the impact on land pricing: The case of the Uemachi fault line in Japan," *Japanese Economic Review* 69(4): 374-393.

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

IPCC, (2021), "Summary for policymakers." In: *Climate Change 2021: The Physical Science Basis*. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 3-32.

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

Kashyap A., and J. Stein, (2000), "What do a million observations on banks say about the transmission of monetary policy?" *American Economic Review* 90(3): 407-428.

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

Koide, Y., K. Nishizaki, and N. Sudo, (2022), "*Suigai risuku ga chika ni oyobosu eikyo*," (Impact of flood risk to land price), Bank of Japan Working Paper Series, No.22-J-10.

Lai, S., Chen, L., Wang, Q. S., and H. Anderson, (2022), "Natural disasters, trade credit, and firm performance," *Economic Modelling* 116: 106029.

Lu, Y., Y. Ogura, Y. Todo, and L. Zhu, (2017), "Supply chain disruptions and trade credit," RIETI DP 17E054.

Nilsen, J. H., (2002) "Trade credit and the bank lending channel," *Journal of Money, Credit and Banking*, 226-253.

Noth, F., and O. Rehbein, (2019), "Badly hurt? Natural disasters and direct firm effects," *Financial Research Letters* 28: 254-258.

Ortega, F., and S. Taşpınar, (2018), "Rising sea levels and sinking property values: Hurricane Sandy and New York's housing market," *Journal of Urban Economics* 106: 81-100.

Rehbein, O., and S. Ongena, (2022), "Flooded through the back door: The role of bank capital in local shock spillovers," *Journal of Financial and Quantitative Analysis 57(7)*, 2627-2658.

Thakor, A., (1996), "Capital requirements, monetary policy, and aggregate bank lending: Theory and empirical evidence," *Journal of Finance* 51(1): 279-324.

Uesugi, I., D. Miyakawa, K. Hosono, A. Ono, and H. Uchida, (2018), "The collateral channel versus the bank lending channel: Evidence from a massive earthquake," Hit-refined working paper No. 79, Hitotsubashi University.

Yamamoto, H., and T. Naka, (2021), "*Suigai ga kigyo zaimu ni ataeru eikyo ni kansuru teiryo bunseki*," (Quantitative analysis on the impact of floods to corporate finance), Bank of Japan Working Paper Series, No. 21-J-3.