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Floods and Loan Reallocation: New Evidence[1]

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Abstract

We examine the impact of severe floods on bank loans, trade credit, investment, and employment using corporate-level panel data of small businesses and bank-level panel data, matched with municipality-level flood damage information. We find that bank loans increase for firms located in a flood area but reduce for physically damaged firms. The former increases the investment for tangible assets after a flood while the latter reduces it. The latter firms increase their dependence on trade credits than bank loans. From the bank-level panel data, we do not document any significant impact of floods on total loans and bank financial soundness. These results imply that loans and resources are reallocated from physically damaged firms to other firms located in nearby safer places, facing recovery demand and fewer competitors.

Keywords: flood, natural disaster, trade credit, bank loans, climate change

JEL Classification: G21, G28, G31, G32, H81, H84, Q54

[1] This study is an outcome of the Research Project on Relationships Between Economic and Social Networks and Globalization at RIETI. We thank insightful comments by the participants at the discussion paper seminar at RIETI.

1. Introduction

The risk of climate change due to the global warming is increasingly eminent. The International Panel of Climate Change (IPCC) Sixth Assessment Report (2021) shows that the increase in the average surface temperature by about one degree Celsius in the last 100 years increased both extreme precipitation and drought globally, and forecasts that this trend will accelerate. In response to this alert, Financial Stability Board (FSB), an international body to coordinate financial regulations and supervisions, published the roadmap to address climate-related financial risks in 2021, which starts with setting a disclosure standard and data collection (FSB 2021).

The effect of climate change is also eminent in Japan. The loss due to flood disasters has increased precipitously in recent years (Figure 1). Japanese government published their scientific projection based on the scenarios in the IPCC report. It shows 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] The purpose of this study is to provide statistical facts about corporate finance after floods, which can serve as the basic information for making policy to alleviate the financial impact of this imminent threat.

Our empirical studies consist of two parts. The first part shows analyses at the corporate level. We use the panel data of about 100 thousand small and medium-sized enterprises (SMEs) in Japan from 2007 to 2020. We investigate the impact of the current and lagged impacts of a severe flood on SMEs' performance, bank loans, trade credits,

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

cash holding, investment, and employment. We detect the deviation from each firm-specific trend due to a flood by linear regressions which control for firm fixed effects, the 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.[2] The statistics report the numerical measures of flood damages at each municipality in each calendar year. We identify the municipalities hit by a severe flood, which is in top 10 percentile in terms of either the number of damaged houses, the total amount of damages, or the ratio of this amount over the taxable income in each municipality.

Floods are often localized and rarely damage the entire part of a municipality. We identify firms physically damaged by a flood among those located in a flood-hit municipality by using the item *Loss on tangible assets* in the income statement of each firm. This item has a non-zero value when a firm suffers a loss from the resale or removal of tangible assets. If a firm reports a non-zero value for this item in the year of a flood or the next year, the removal or resale of tangible assets is plausibly due to flood damage.[3] This item enables us to identify firms physically damaged by a flood, although it tends to underestimate the damage since SMEs often keep using old machinery over statutory useful life, whose book value is zero.

The second part of the study is the bank-level analysis. We calculate the ratio of SME borrowers located in a 10-percentile flood area for each bank from the above corporate database. This ratio serves as a measure for each bank's exposure to a flood. We estimate the deviation from each bank trend due to the exposure to a flood in terms of total loan

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

[3] We owe this idea to Uesugi et al (2018), which use the loss on tangibles to measure the physical damage of firms and banks from an earthquake.

growth, deposit growth, the liquidity ratio and the non-performing loan ratio by a linear regression after controlling for the bank and 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 provided by the other firms to fill in the reduced bank loans. Both groups of firms, especially those not physically damaged, increase their cash holding after a flood. Those located in a flood area but not physically damaged increase investment and employment after a flood, while those physically damaged reduce investment and keep the same level of employment as before a flood. From the bank-level analysis, we do not find any significant impact of a flood on banks' lending behavior and financial soundness, even if we restrict our full sample to a subsample of small regional cooperative banks (Shinkin banks).

These results imply that banks, including small local banks, shift their loans from the firms whose collateral values are damaged by a flood to those in the same municipality but not physically damaged, thus facing reconstruction demand and reduced competitors.[4] Trade credit from the latter serves as a substitute for bank loans for those physically damaged by a flood.

Additional analyses show that both payables and receivables increase after a flood. In particular, when suppliers or customers are physically damaged by a flood. This result implies the existence of a domino effect of trade credits, i.e., a stop in cash payment at a firm triggers an increase in payables throughout the supply-chain network. We also find

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[4] Koide et al (2022) provide evidence for the negative impact of a flood to land price.

that government-controlled banks (including Development Bank of Japan, Japan Finance Corporation, and Shoko-Chukin Bank), which provide government-subsidized loans for disaster-hit areas, indeed increase long-term loans for an area hit by a severe earthquake. However, such an effect is not visible in an area hit by a flood.

The remainder of this paper is organized as follows. In Section 2, we review the pertinent literature. Section 3 is the description of our dataset. Section 4 and Section 5 discuss results of the corporate- and bank-level analyses. Section 6 offers policy implications. Section 7 concludes.

2. Literature

Several empirical studies examine the impact of floods on corporate finance using the US county-year panel data, constructed from the Spatial Hazard Events and Losses Database (SHELDUS), or the German county-year panel data before and after the Elbe Flood in 2013. Studies using US data consistently find that banks increase loans for firms or individuals located in a flood area, while they reduce loans to other areas, in particular, non-core markets for each bank (Cortes et al. 2017). This reduction is more significant for under-capitalized banks (Ivanov et al. 2020). They also find that the loan rate increases more than the deposit rate leading to an increase in net interest margin in flood-hit areas (Barth et al. 2019), and that banks increase sales of liquid loans (Cortes et al. 2017), or increase their dependence on brokered deposits (Barth et al. 2019) to finance recovery loans.

Studies with German data also find a similar result. Banks exposed to a flood-affected area increase loans (Koetter et al. 2020). Lower-capitalized banks exposed to a flood reduce their lending to outside of flood areas (Rehbein and Ongena 2022). On the other hand, Noth and Rehbein (2019) find a positive impact on corporate sales and cash holding in a flood area.

Our analyses using the dataset in Japan, a typical bank-dependent economy where we observe increasing flood disasters, offer supporting evidence for the increased bank lending after a flood, particularly by those whose core market is exposed to a flood.[5] Notably, we also obtain several new findings. First, we find that the increased loans are directed to those who are located in a flood-hit municipality but not physically damaged, rather than those whose tangible assets are damaged. In other words, we document a loan reallocation within a disaster-hit area from those directly damaged to those not. This loan reallocation promotes the reallocation of capital and employment. Second, we find that trade credit serves as a substitute for bank loans, especially for those physically damaged and run in short of bank loans. The reduction of loans for physically damaged firms is consistent with the existing evidence for the damage to collateral values after a public indication of the flood hazard and an actual flood disaster (Hino and Smith 2005, Gu et al. 2017, Ortega and Taspinar 2018, Koide et al. 2022, and Saito et al. 2007, Uesugi 2018).

Examining the short-term liquidity management after the unexpected heavy snow in the northeast US in 2014 and 2015, Brown et al. (2021) find that firms respond to the negative cash-flow shock by increasing both drawdown and facility size of credit lines by paying higher interest rates during nine months after the disaster. Our result that firms depend more on trade credit comes from the difference in the convention in SME financing between the US and Japan. While US SMEs use credit lines extensively, Japanese SMEs rarely use credit lines, and no interest is required for trade credits in Japan.

The existing studies also provide evidence for bank lending behavior after other

[5] The empirical studies in Japan about floods are still scarce. Recently, Yamamoto and Naka (2021) report the impact of floods on corporate sales and profits with the corporate-level panel data. They report that the impact to sales is negative but not statistically significant, but that the impact on the profit rate is negative and significant for the manufacturing sector.

types of natural disasters. From the dataset before and after the earthquake in Japan, Hosono et al. (2016) find that, among firms located outside of earthquake-hit areas, firms reduce investments to a greater extent if their main bank is located in a damaged area than otherwise. Uesugi et al. (2018) find that firms with damaged tangible assets reduce borrowing from banks due to the reduction in collateral values. Lu et al. (2017) find the chain increase in both payables and receivables through the supply-chain network after an earthquake. Berg and Schrader (2012) find a significant increase in loan applications and the significant reduction in the approval rate after a volcano eruption in Ecuador. They find that this increased borrowing constraint is mitigated by the pre-existing bank-firm relationship. While these disasters bring more severe damages than floods, they are not directly related to climate change and occur less frequently.

3. Data

3.1. Identification of areas severely hit by floods

We collect the flood damage information in Japan from the Statistics of Flood Damage,[6] compiled by the Ministry of Land, Infrastructure, Transport, and Tourism (MLIT), Japan. The statistics report the numerical measures of flood damages at the municipality level in each calendar year. The measures include the squares of inundated areas, the number of damaged houses, the amounts of damages in the private sector, such as loss on assets and agricultural products, and the loss due to a temporary shut-down, and the amounts of damages to the public infrastructure.

We focus on three measures: i) the number of damaged houses, ii) total amount of

[6] If municipalities are merged during the sample period, we treat these municipalities as one municipality throughout our sample period. The statistics report ward-level values after 2009 for government ordinance designated cities, i.e., major cities, except for Tokyo, despite that it reports the city-level values until 2009. We aggregate to the city-level values for these cities after 2009.

damages, including both in the private sector and in the public infrastructure, and iii) the ratio of this amount over the taxable income in each municipality. The first two capture the absolute size of a damage, whereas the last one captures the size of a damage relative to the size of each municipality. To calculate the last measure, we collect the taxable income information from Nikkei NEEDS FinancialQuest.[7]

Among the municipalities that report any flood damages from 2006 to 2019, we specify municipalities as areas severely hit by a flood if their report of any of the three damage measures is at the 10 percentile or higher. The percentile is calculated from the entire sample period to capture the increasing trend of the severity of floods.[8]

To match this information with the corporate financial statement data, we need to identify the month of each flood. For this purpose, we refer to the list of prefectures, year, and month where and when the Disaster Relief Act (DRA) was applied for a flood in the White Paper on Disaster Management 2021.[9] If a municipality with a 10-percentile damage belongs to a prefecture in this table, we assign the month indicated in this table as the month of the flood for such a municipality. We augment with the month information hand-collected from newspaper articles and municipality websites for those that cannot be matched with the DRA table. We also construct a dummy variable from the DRA table to indicate areas damaged by an earthquake to control for the effect of earthquakes.

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[7] We observe many mergers among municipalities in the 2000s. We aggregate the values of pre-merger municipalities to that of a municipality as of 2021 by following the data collection rule in Nikkei NEEDS. We use the municipality level data, instead of the ward level data, for each large cities with wards except Tokyo (ordinance designated cities), since the ward-level taxable income data is not available except for Tokyo.

[8] We also try the 1-percentile and the 5-percentile criteria and obtain the results similar to those we present later. Results based on these criteria are available upon request.

[9] 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.

3.2. Corporate information

We collect corporate information, including financial statements, location, and bank relationship from Tokyo Shoko Research (TSR) Corporate Financial Database and Corporate Basic Information Database from 2007 to 2020. We also collect the list of 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 headquarter 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 the Nikkei NEEDS FinancialQuest. We identify lending banks for each firm from the list of 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 10-percentile flood area for each bank, which we call *exposure10.* In addition, the municipalities of bank headquarters are identified by 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 1 if the head office of a main bank is located in a municipality hit by an earthquake at time *t*, 0 otherwise.

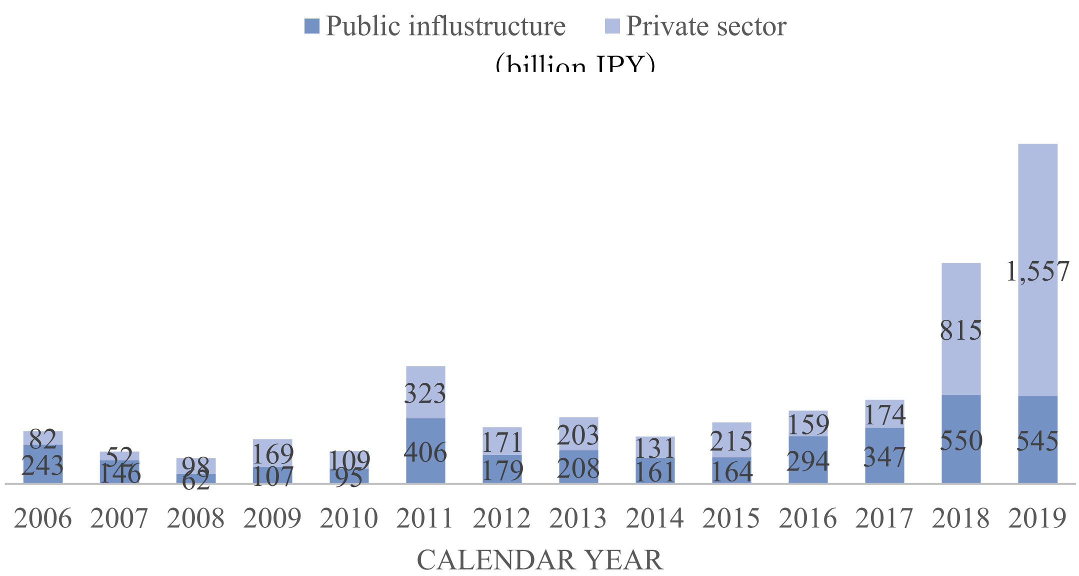
3.4. Descriptive statistics

3.4.1. Flood data

Figure 1 is the time-series plot of the aggregate amounts of flood damages in our data period. The figure shows an increasing trend of flood severity and prevalence in Japan. We observe the huge damage amounts in the last consecutive two years, i.e., 2018 (1.4 trillion JPY), due to the heavy rain in the western part of Japan in July, and 2019 (2.1 trillion JPY), due to the Typhoon Hagibis, which passed through almost the entire of Japan in October. Both losses exceed 10 billion USD under the exchange rate of 130 JPY per 1 USD.

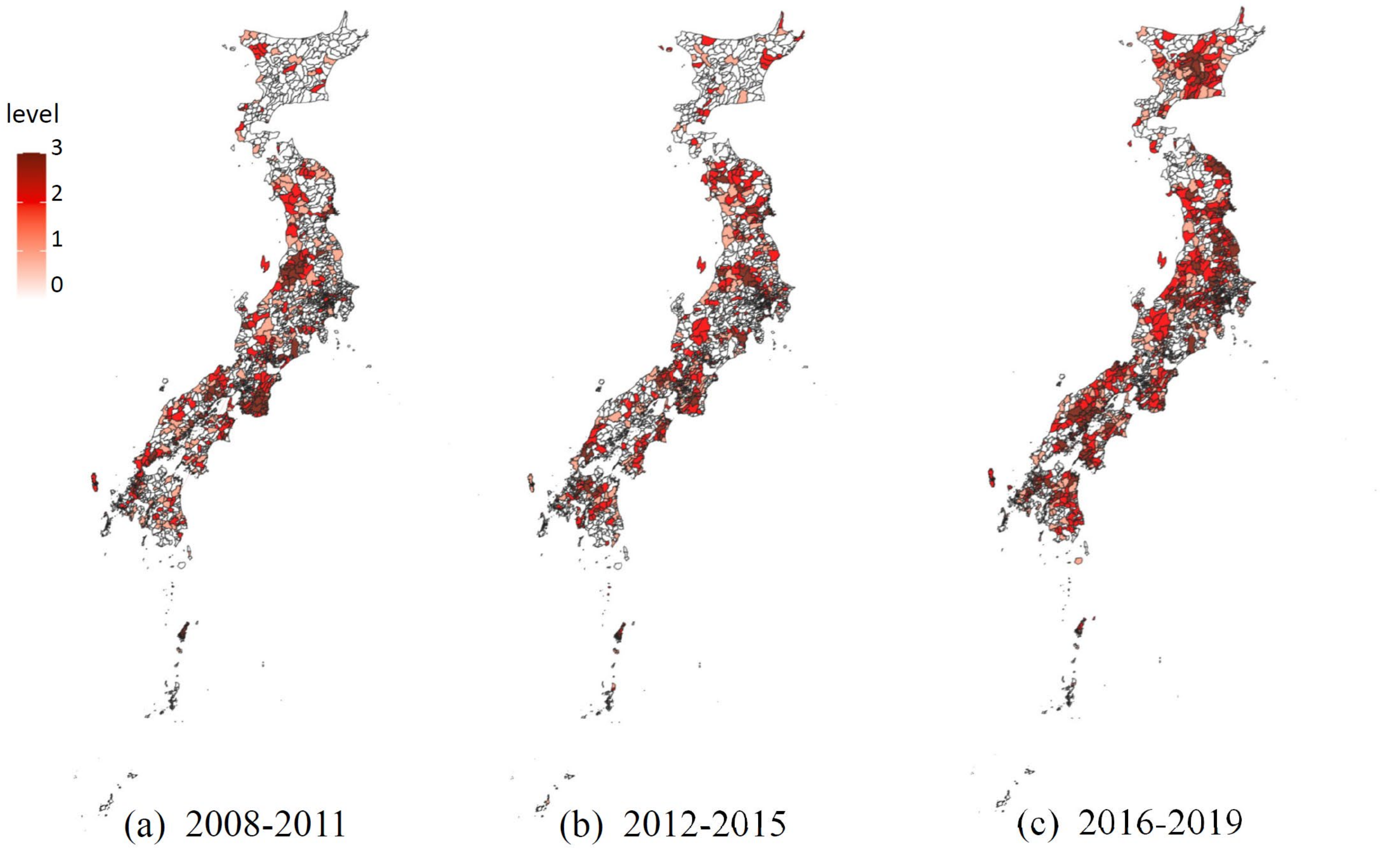
Figure 2 is the map of municipalities damaged by floods. The darker color indicates more severe damage. The figure shows that the severity and the breadth increase in Panel (c) 2016-2019, especially in the northern part of Japan.

Figure 1. Aggregate damages from floods in Japan



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

Figure 2: Municipalities suffered from floods



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

(Note) Level 3 indicates the 1percentile-damage areas, level 2 indicates the 5percentile-damage areas, and leve11 indicates the 10 percentile-damage areas.

3.4.2. *Corporate data*

We focus on small and medium-sized enterprises (SMEs) with employees of less than 300, since their facilities are locally located and more likely to be affected by floods. We exclude those in the financial, insurance, and real estate sector because their accounting system or financial structure differ from other industrial companies. We also exclude outliers as we describe later. We set our estimation window for our regressions from 2010 to 2020 to avoid the effect of the Global Financial Crisis from 2007 to 2009.

Table 1 shows the number of sample firms in our dataset. The total number of firms increases until 2014 due to TSR's efforts to increase their data coverage. The number of firms in 2020 is smaller than the other years because the database is available until March 2020. We keep these observations in 2020 since the flood season in Japan is from June to October, and we can identify whether each of these observations is in flood areas or not. It is consistent with the aggregate flood damage data that the ratio of firms located in 10 percentile-damage areas is very high from 2018 to 2020 (second last column in Table 1). Among those located in 10 percentile-damage areas, about 17% of firms report non-zero loss on tangible assets (last column in Table 1).

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

(Note) Number of observations is calculated after dropping outliers above 99 percentile and below 1 percentile in each year with respect to sales growth rate. Column (2) indicates the number of firms that reported non-zero loss on tangible assets among those located in 10-precentile-damage areas.

Year	(1) 10pct-damage	(2) 10pct-damage & tangible loss	(3) Others	(4) Total	(1)/(4) (%)	(2)/(1) (%)
2010	3,156	644	53,093	56,249	5.6	20.4
2011	4,921	1,023	64,661	69,582	7.1	20.8
2012	6,902	1,475	72,531	79,433	8.7	21.4
2013	4,253	754	87,241	91,494	4.6	17.7
2014	9,421	1,806	93,183	102,604	9.2	19.2
2015	6,677	994	99,938	106,615	6.3	14.9
2016	4,753	611	101,388	106,141	4.5	12.9
2017	5,249	794	100,608	105,857	5.0	15.1
2018	12,015	1,757	91,626	103,641	11.6	14.6
2019	11,320	1,585	83,045	94,365	12.0	14.0
2020	5,661	931	22,903	28,564	19.8	16.4
Total	74,328	12,374	870,217	944,545	7.9	16.6

One feature of our dataset is the industrial composition. As Table 2 shows, more than half of our sample firms are in the construction sector. This is by far larger than the share observed in the Economic Census. On the other hand, the retail/wholesale and service sectors are highly under-representing the population. The over-representation of the construction sector in our dataset comes from our requirement for the availability of detailed financial statements and the fact that construction firms tend to keep a well-documented accounting information as it is the requirement for participation in public contracts. These features necessitate a robustness check on this point.

In this study, we focus on the impact of floods to corporate finance, i.e., bank loans, trade credit, and cash holding, investment, and employment. The definition of the variables to measure these aspects and to control for firm or main bank characteristics are listed in Table 3(a).

Table 2. Industrial composition

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

	Our dataset	**Economic Census**
Agriculture/forestry/fishery	0.7%	0.6%
Mining	0.1%	0.1%
Construction	59.9%	8.0%
Manufacturing	11.9%	13.9%
Information/communication	1.3%	2.3%
Transportation	1.8%	4.4%
Retail/wholesale	14.9%	28.9%
Service	9.3%	37.1%

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 reported number of damaged houses, ii) the ratio of loss amounts over taxable income, or iii) the loss amounts, is at the # (=1, 5, or 10) percentile or higher during the accounting period, or 0 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 reported number of damaged houses, ii) the ratio of loss amounts over taxable income, or iii) the loss amounts, is at the # (=1, 5, or 10) percentile or higher, and (2) the firm reports a loss on their tangible asstes, during the accounting period, or 0 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 0 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) - lont-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) *	TSR (Corporate financial data)

	100 (%).	
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 exposure1	Exposure to a flood with 1 percentile damage (damage1 = 1) of a main bank. Exposure is the ratio of borrowers located in a municipality with 1 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 hit by an earthquake among all borrowers identified by TSR. Main bank is the first one in the list of lenders.	Earthquake information: White Paper on Disaster Management 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, 0 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), 0 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	TSR (Corporate basic information).

	in the current year, 0 otherwise.	
Ratio of damaged customers (#%)	Ratio of corporate customers who are located in a municipality hit by a flood with # (=1,5, or 10) percentile damage (damage# =1).	TSR (Corporate Relation Data, Corporate Basic Information), Flood Disaster Statistics (MILT).
Ratio of damaged suppliers (#%)	Ratio of suppliers who are located in a municipality hit by a flood with # (=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	Non-performing 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.
exposure10	Asset-weighted ratio of borrowers located in a top 10-percentile flood-damaged municipality.	Flood Disaster Statistics (MLIT), TSR, White Paper on Disaster Management 2021 (Cabinet Office).
B exposure_quake	Asset-weighted ratio of borrowers located in a municipality damaged by a earthquake designated by the Disaster Relief Act.	TSR, White Paper on Disaster Management 2021.
B HQ hit by 10pc flood	A dummy indicating the headquarter of the main bank is located in a municipality hit by a 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 bank headquarter is located in a municipality hit by an earthquake designated by the Disaster Relief Act.	TSR, White Paper on Disaster Management 2021.

Table 4. Descriptive statistics

(a) Corporate-level data

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

	N	Mean	SD	Min	p1	p50	p99	Max
loan/asset	1,055,055	0.378	0.409	0.000	0.000	0.290	1.906	4.557
Δloan/asset	1,055,055	0.102	0.214	-0.364	-0.180	0.019	0.969	2.342
Δlong-term loan/asset	1,055,055	-0.001	0.109	-4.000	-0.238	0.000	0.397	2.280
short-term loan/asset	1,055,055	0.102	0.192	0.000	0.000	0.008	0.926	4.294
trade credit/asset	1,055,055	-0.071	0.155	-1.104	-0.551	-0.051	0.304	0.899
payable/asset	1,055,055	0.139	0.149	0.000	0.000	0.092	0.656	0.985
receivable/asset	1,055,055	0.210	0.175	0.000	0.000	0.173	0.759	1.117
Δtrade credit/asset	1,055,055	-0.001	0.100	-0.986	-0.310	0.000	0.293	0.946
Δpayable/asset	1,055,055	0.005	0.079	-0.337	-0.209	0.000	0.290	0.591
Δreceivable/asset	1,055,055	0.006	0.107	-0.421	-0.281	0.000	0.374	0.720
sales/asset	1,055,055	1.714	1.102	0.067	0.266	1.452	5.696	11.072
Δsales/asset	1,055,055	0.024	0.467	-8.397	-1.336	0.009	1.466	6.755
sales growth rate	1,055,055	0.037	0.260	-0.701	-0.506	0.008	0.984	1.974
cash hold	1,055,055	0.523	0.750	0.000	0.000	0.282	3.785	9.697
Δcash hold	1,055,055	0.020	0.226	-1.529	-0.685	0.004	0.781	1.780
special income/asset	1,055,055	0.382	3.836	-4.080	0.000	0.000	7.979	1764.599
tangible loss/asset	1,055,055	0.028	0.160	0.000	0.000	0.000	0.847	2.918
I/K	1,055,055	-0.010	0.063	-0.301	-0.181	-0.010	0.238	0.543

employee	1,055,055	26.652	41.359	0	1	11	220	299
Δemployee	1,055,055	0.201	2.941	-31	-9	0	12	54
liability/asset	1,055,055	0.676	0.512	-0.011	0.012	0.642	2.484	86.269
credit score	1,054,846	50.790	6.536	8	37	50	67	86
cash flow/tangible asset	802,500	5.491	408.436	-38013.0	-7.3	0.2	41.2	166339.0
cash flow/#employees	811,717	1.361	6.098	-812.0	-3.3	0.7	12.6	1976.5
ec_tangible	1,055,045	38.531	191.993	-1.0	2.4	21.2	272.8	60688.0
ec_employee	1,041,530	265.521	17036.530	-808486.0	-0.5	5.9	1616.2	9550184.0
MB exposure1	978,540	0.009	0.037	0.000	0.000	0.000	0.176	0.901
MB exposure_quake	978,540	0.035	0.110	0.000	0.000	0.000	0.580	0.988
MB HQ hit by quake	975,157	0.025	0.156	0.000	0.000	0.000	1.000	1.000
MB HQ hit by 1pc flood	975,157	0.017	0.131	0.000	0.000	0.000	1.000	1.000
MB liquidity ratio	1,011,633	41.381	13.873	5.187	20.761	39.947	97.025	97.854
MB leverage ratio	1,011,633	5.340	1.390	1.104	2.792	5.170	9.718	24.836
government bank	1,055,055	0.095	0.293	0	0	0	1	1
Ratio of damaged customers (10%)	1,011,447	0.014	0.076	0.000	0.000	0.000	0.333	1.000
Ratio of damaged suppliers (10%)	1,011,447	0.014	0.076	0.000	0.000	0.000	0.333	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					

To avoid the outliers in terms of financial variables, we drop those below one percentile and above 99 percentile in each year from our analysis, with respect to the variables: *loan/asset*, *Δloan/asset*, *payable/asset*, *receivable/asset*, *Δpayable/asset*, *Δreceivable/asset*, *sales/asset*, *sales growth rate*, *cash hold*, *Δcash hold*, *tangible loss/asset*, *cash flow/tangible asset*, *cash flow/#employees*, *ec_tangible*, *ec_employee*, I/K, and *Δemployee*. The descriptive statistics after dropping these outliers are listed in Table 4(a).

3.4.3. Bank data

Table 4(b) is the list of the descriptive statistics of banks in our dataset. The definition of each variable is listed in Table 3(b). We do not drop any outliers. The asset size of banks ranges from 20 billion JPY (about 150 million USD, 1USD = 135 JPY) to 89 trillion JPY (about 660 trillion USD). Most of SMEs in our corporate dataset 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. Liquidity ratio ranges from 9% to 90%. Some small cooperative banks show extremely high liquidity ratio because they are specialized in security investments. NPL ratio ranges from 0.1% to 23%. Leverage ratio (capital in B/S over total asset) ranges from 1% to 24%. Most of extreme values come from small cooperative banks. The exposure to the 10-percentile flood and the exposure to a severe earthquake designated by the Disaster Relief Act are concentrated in the top 5% observations. Headquarters of 2.5% of 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 sales growth rate on the leads and lags of *damage10*, the dummy to indicate that a firm is in a 10-percentile flood area with firm fixed effect and industry-year fixed effect (Column (1), Table 5). The estimated coefficients indicate that sales increase in the year of a flood and the next year. This indicates a significant reconstruction demand. As for an earthquake, the estimates indicate a similar pattern: sales in the next year after an earthquake increase significantly. The coefficient is by far larger in an earthquake than in a flood. This indicates a greater extent of damage in an earthquake.

To see how the over-representation of the construction sector in our dataset, 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, especially in the construction and the service sector. The table also shows that sales increase in all sectors after an earthquake.

To see the possible impact of government subsidies or insurances, we also regress special income/asset on the lead and lags of damage10 (Column (2), Table 5). The coefficient is positive and significant only one year later of an earthquake. None of the coefficients are significant for floods. The significant coefficient for the earthquake indicates the impact of the massive public subsidies.

To detect the physical damages by floods, we regress the loss on tangible assets, which is reported in the income statement. The result (Column (3), Table 5) shows that firms tend to report in the next year of earthquakes. This pattern is similar but weaker in floods.

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

(Notes) Estimated coefficients are listed. Estimated constant is omitted. Dependent variable is indicated at the top of each column. "f1” in the list of explanatory variables indicates one-year lead, i.e., a year before a 10-percentile flood, “l1” indicates one-year lag, i.e., a year after a 10 percentile flood, and “l2” indicates two-year lag. The two-way (firm and year*industry) clustered standard errors are in parentheses. Industry classification is based on Japan Standard Industrial Classification 2 digit (Chu-Bunrui). Constant term is omitted from the report. *** p<0.01, ** p<0.05, * p<0.1 (two-sided).

Variables	(1) sales growth rate	(2) special income/asset	(3) tangible loss/asset
damage10(t+1)	0.0001	-0.0151	-0.0011
	(0.0023)	(0.0126)	(0.0007)
damage10(t)	0.0086***	-0.0123	-0.0007
	(0.0023)	(0.0150)	(0.0008)
damage10(t-1)	0.0077**	-0.0115	0.0013
	(0.0030)	(0.0127)	(0.0009)
damage10(t-2)	0.0004	-0.0068	-0.0001
	(0.0022)	(0.0125)	(0.0009)
hit_quake(t+1)	0.0038	0.0139	-0.0032*
	(0.0078)	(0.0188)	(0.0018)
hit_quake(t)	0.0033	0.0068	-0.0021
	(0.0054)	(0.0257)	(0.0020)
hit_quake(t-1)	0.0632***	0.0602*	0.0032*
	(0.0167)	(0.0332)	(0.0016)
hit_quake(t-2)	-0.0054	-0.0155	0.0020
	(0.0065)	(0.0236)	(0.0019)
N	676,251	676,251	676,251
Adj. R-sq.	-0.0842	0.1580	0.1016
year*industry fe	yes	yes	yes
firm fe	yes	yes	yes

Table 6. Sales growth by industry.

(Notes) Estimated coefficients are listed. Estimated constant is omitted. Dependent variable is sales growth rate. The two-way (firm and year) clustered standard errors are in parentheses. Constant term is omitted from the report. *** p<0.01, ** p<0.05, * p<0.1 (two-sided).

Variables	(1) Construction	(2) Manufacturing	(3) Wholesale/retail	(4) Service
damage10(t+1)	-0.0018	0.0034	0.0045	0.0053*
	(0.0037)	(0.0043)	(0.0031)	(0.0024)
damage10(t)	0.0103**	0.0056	0.0062	0.0087***
	(0.0037)	(0.0038)	(0.0046)	(0.0024)
damage10(t-1)	0.0121**	-0.0023	0.0011	0.0028
	(0.0044)	(0.0032)	(0.0060)	(0.0032)
damage10(t-2)	-0.0007	-0.0020	0.0101*	0.0019
	(0.0035)	(0.0060)	(0.0054)	(0.0025)
hit_quake(t+1)	-0.0010	0.0138**	0.0110***	0.0033
	(0.0148)	(0.0045)	(0.0031)	(0.0067)
hit_quake(t)	0.0077	-0.0062	0.0074	-0.0021
	(0.0118)	(0.0042)	(0.0067)	(0.0044)
hit_quake(t-1)	0.0988***	0.0109*	0.0330***	0.0382***
	(0.0105)	(0.0054)	(0.0053)	(0.0074)
hit_quake(t-2)	-0.0048	-0.0090**	-0.0094*	0.0090*
	(0.0117)	(0.0036)	(0.0043)	(0.0048)
N	403,730	82,896	104,617	58,193
Adj. R-sq.	-0.1044	-0.0259	0.0057	-0.0320
year fe	yes	yes	yes	yes
firm fe	yes	yes	yes	yes

4. Corporate-level analysis

4.1. Estimation model

To see the impact of floods on corporate funding structure and investment behavior, we estimate their deviations from each firm-specific trend due to a flood by the following linear regression.

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

where i is the index of firms, t is year, y_{it} is a measure of corporate funding or investment, which will be described later, $damage10_{it}$ is a dummy variable indicating firm i is located in a 10 percentile flood area in year t, X_{it} is the vector of control variables and β_4 is the vector of the coefficients of them, η_{st} is the sector times 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 the 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 located in an area hit by an earthquake designated by DRA.

Firm characteristics include the indicators of credit quality, *leverage*, and *credit score* assigned by TSR, and the growth potential measured by the past and current increase in sales divided by total assets in the previous year, *Δsales/asset*. For the investment or employment regression, we follow Bloom et al. (2007) for the choice of explanatory variables. We include the current sales growth rate and its squared term in place of *Δsales/asset*, the current and past cash flow per tangible asset (employee for the employment regression), and an error-correction term, which is defined as a deviation rate between sales and tangible assets (the number of employees for the employment regression).

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

4.2. Funding structure after floods

4.2.1. Bank loan

4.2.1.1. Baseline

Table 7 shows the results of the baseline regressions about the corporate funding structure after a flood. Bank loans increase in the year of a flood (Column 1). This is mostly driven by the long-term loan (Column 2). The short-term loan rather reduces after a flood (Column 3).[10]

As for the control variables, the coefficients of *hit_quake*, the indicator of an earthquake, show the similar but stronger pattern as a flood. Firms with better credit quality, high score and low leverage, tend to use long-term loans, while those with lower credit quality tend to use short-term loans. Firms with growing sales reduce their dependence on bank loans. Among the control variables regarding main bank (MB) characteristics, both MB liquidity ratio and MB leverage ratio have a negative and significant coefficient. These coefficients appear to capture a reverse causality, i.e., the liquidity ratio, a ratio of liquid assets over total

[10] 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.

assets including loans, and the leverage ratio, the ratio of capital over total assets, reduce for banks that increase lending aggressively.

Table 7. Loans after a flood: Baseline

(Notes) Estimated coefficients are listed. Dependent variable is indicated at the top of each column. Firm and sector-year two-way clustered standard errors in parentheses. Constant term is omitted from the report. *** 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)	0.0020***	0.0019***	0.0000
	(0.0006)	(0.0005)	(0.0003)
damage10(t-1)	-0.0003	0.0006	-0.0010**
	(0.0008)	(0.0007)	(0.0005)
damage10(t-2)	-0.0004	0.0008	-0.0013**
	(0.0007)	(0.0006)	(0.0005)
hit_quake(t)	0.0105***	0.0087***	0.0018
	(0.0022)	(0.0012)	(0.0016)
hit_quake(t-1)	0.0014	0.0026**	-0.0012
	(0.0014)	(0.0012)	(0.0007)
hit_quake(t-2)	-0.0053***	-0.0022*	-0.0031**
	(0.0016)	(0.0012)	(0.0012)
leverage(t-1)	0.0812***	-0.0641***	0.1453***
	(0.0064)	(0.0050)	(0.0036)
score(t-1)	-0.0003*	0.0009***	-0.0013***
	(0.0002)	(0.0001)	(0.0001)
Δsales/asset(t-1)	-0.0086***	0.0004	-0.0090***
	(0.0008)	(0.0006)	(0.0005)
Δsales/asset(t)	-0.0207***	-0.0102***	-0.0105***
	(0.0012)	(0.0008)	(0.0007)
MB exposure1(t)	0.0055**	0.0032	0.0024
	(0.0027)	(0.0019)	(0.0017)

MB exposure_quake(t)	0.0067	0.0080**	-0.0013
	(0.0055)	(0.0035)	(0.0032)
MB in quake(t)	-0.0055*	-0.0074***	0.0019
	(0.0031)	(0.0013)	(0.0025)
MB in 10pc flood(t)	-0.0003	-0.0008	0.0005
	(0.0008)	(0.0007)	(0.0005)
MB liquidity ratio(t)	-0.0001**	-0.0000	-0.0001***
	(0.0001)	(0.0000)	(0.0000)
MB leverage ratio(t)	-0.0019***	-0.0009**	-0.0010***
	(0.0005)	(0.0004)	(0.0003)
N	873,864	873,864	873,864
Adj. R-sq.	0.6377	0.0291	0.7983
year*industry fe	yes	yes	yes
firm fe	yes	yes	yes

4.2.1.2. 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 as usual. To see whether the increase in loans comes from those firms whose assets are physically damaged by a flood or from other firms outside a damaged area within a municipality, we introduce the interaction term of *damage10*, a dummy to indicate a 10-percentile flood, and *tangible loss*, a dummy variable, which equals one if a firm reports a non-zero loss on their tangible asset. We also include the current and lagged *tangible loss* into the 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 are listed. Dependent variable is 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 s.e. in parentheses. Constant is omitted. *** 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)	0.0022***	0.0021***	0.0001
	(0.0006)	(0.0005)	(0.0004)
damage10(t-1)	0.0001	0.0011	-0.0009*
	(0.0009)	(0.0008)	(0.0005)
damage10(t-2)	-0.0004	0.0010	-0.0014**
	(0.0008)	(0.0007)	(0.0007)
damage10*tangible loss(t)	-0.0011	-0.0007	-0.0004
	(0.0011)	(0.0009)	(0.0009)
damage10*tangible loss(t-1)	-0.0024*	-0.0021*	-0.0003
	(0.0015)	(0.0012)	(0.0009)
damage10*tangible loss(t-2)	-0.0003	-0.0008	0.0004
	(0.0016)	(0.0012)	(0.0012)
hit_quake(t)	0.0114***	0.0097***	0.0017
	(0.0023)	(0.0013)	(0.0017)
hit_quake(t-1)	0.0018	0.0027**	-0.0010
	(0.0016)	(0.0013)	(0.0010)
hit_quake(t-2)	-0.0063***	-0.0029**	-0.0034**
	(0.0018)	(0.0014)	(0.0014)
hit_quake*tangible loss(t)	-0.0035	-0.0037**	0.0002
	(0.0021)	(0.0016)	(0.0013)
hit_quake*tangible loss(t-1)	-0.0014	-0.0006	-0.0008
	(0.0022)	(0.0015)	(0.0015)
hit_quake*tangible loss(t-2)	0.0037	0.0026	0.0011
	(0.0025)	(0.0018)	(0.0017)
N	873,864	873,864	873,864
Adj. R-sq.	0.6377	0.0292	0.7983
Controls	yes	yes	yes
year*industry fe	yes	yes	yes
firm fe	yes	yes	yes

Table 8 shows the results of this regression analysis. The coefficients of *damage10* and its lags show the same pattern as Table 7. However, the interaction term of *damage10* and *tangible loss* shows a negative coefficient in the current, next year, and two years later of a flood. The coefficient is statistically significant in the next year. This result implies that, while firms located in a municipality hit by a flood increase their borrowings, physically damaged firms do not. Rather, they even reduce borrowing from banks. We find a similar pattern for an earthquake. A potential explanation for this result is that the damage to collateral values due to a disaster has reduced borrowing from banks.[11]

Later in Section 5, we present a result that there is no significant change in bank lending in the bank-level analyses. This result and the previously discussed one based on the *damage10* and *tangible loss* interaction term indicate that banks shift their lending from borrowers physically damaged by a disaster to those who are located nearby but are not physically damaged, and face a strong reconstruction demand with smaller number of competitors.

4.2.1.3. 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 the driving force, we augment the above regressions with the interaction terms of the dummy to indicate a main bank headquarter is located in a municipality hit by a 10-percentile flood, *MB in 10pc Flood*, with the flood dummies that we have used so far. The results are reported in Table 9. The estimated coefficients of *damage10* and its interaction term with *tangible loss* show the similar pattern as those in Table 8, although the statistical significance is weaker than those in Table 8. Most of the interaction terms of a MB-in-flood dummy with flood dummies do not have any significant coefficients. On balance, we can conclude that the results so far are primarily driven by firm factors rather than bank factors.

[11] Uesugi et al (2018) provides evidence that the collateral damage due to the Great East Japan Earthquake in 2011 significantly reduced bank loans.

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

(Notes) Estimated coefficients are listed. Dependent variable is indicated at the top of each column. MB in 10pc flood is a dummy variable to indicate the headquarter of the main bank is located in a municipality hit by a 10-percentile flood. Control variables include those in Table 8. Firm and sector-year two-way clustered standard errors in parentheses. Constant term is omitted. *** 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)	0.0020**	0.0020***	-0.0000
	(0.0009)	(0.0007)	(0.0006)
damage10(t-1)	0.0007	0.0013	-0.0006
	(0.0011)	(0.0008)	(0.0007)
damage10(t-2)	-0.0000	0.0015*	-0.0016**
	(0.0011)	(0.0009)	(0.0008)
damage10*tangible loss(t)	-0.0027	-0.0026**	-0.0001
	(0.0017)	(0.0012)	(0.0012)
damage10*tangible loss(t-1)	-0.0022	-0.0018	-0.0004
	(0.0017)	(0.0015)	(0.0010)
damage10*tangible loss(t-2)	-0.0000	-0.0013	0.0012
	(0.0022)	(0.0016)	(0.0015)
damage10*MB in 10pc flood(t)	0.0008	0.0003	0.0005
	(0.0016)	(0.0014)	(0.0011)
damage10*MB in 10pc flood(t-1)	-0.0012	-0.0004	-0.0008
	(0.0014)	(0.0010)	(0.0010)
damage10*MB in 10pc flood(t-2)	-0.0009	-0.0014	0.0004
	(0.0017)	(0.0013)	(0.0009)
damage10*tangible loss	0.0030	0.0041*	-0.0011
*MB in 10pc flood(t)	(0.0028)	(0.0021)	(0.0023)
damage10*tangible loss	-0.0005	-0.0006	0.0001
*MB in 10pc flood(t-1)	(0.0026)	(0.0016)	(0.0019)
damage10*tangible loss	-0.0005	0.0010	-0.0015
*MB in 10pc flood(t-2)	(0.0034)	(0.0024)	(0.0022)
Observations	868,519	868,519	868,519
Adjusted R-squared	0.6380	0.0289	0.7984
Controls	yes	yes	yes
year*industry fe	yes	yes	yes
firm fe	yes	yes	yes

Table 10. Loans after a flood: Government-controlled Banks

(Notes) Estimated coefficients are listed. Dependent variable is indicated at the top of each column. Control variables includes the government-bank dummy and those in Table 7 except for main bank attributes. Firm, sector-year, bank-year three-way clustered s.e. in parentheses. Constant term is omitted. *** 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)	0.0024***	0.0018***	0.0006
	(0.0006)	(0.0005)	(0.0004)
damage10(t-1)	-0.0004	0.0000	-0.0004
	(0.0009)	(0.0006)	(0.0005)
damage10(t-2)	-0.0000	0.0005	-0.0006
	(0.0007)	(0.0006)	(0.0006)
damage10(t)	-0.0008	0.0009	-0.0017
*government bank(t)	(0.0015)	(0.0012)	(0.0013)
damage10(t-1)	-0.0002	0.0013	-0.0015
*government bank(t)	(0.0018)	(0.0013)	(0.0011)
damage10(t-2)	-0.0022	-0.0017	-0.0005
*government bank(t)	(0.0013)	(0.0011)	(0.0009)
hit_quake(t)	0.0061***	0.0040***	0.0020**
	(0.0016)	(0.0015)	(0.0008)
hit_quake(t-1)	-0.0010	-0.0027**	0.0017
	(0.0014)	(0.0011)	(0.0012)
hit_quake(t-2)	-0.0003	-0.0011	0.0008
	(0.0014)	(0.0012)	(0.0012)
hit_quake(t)	0.0040	0.0050	-0.0010
*government bank(t)	(0.0034)	(0.0033)	(0.0012)
hit_quake(t-1)	0.0001	0.0043**	-0.0042**
*government bank(t)	(0.0023)	(0.0020)	(0.0018)
hit_quake(t-2)	-0.0042*	-0.0005	-0.0037***
*government bank(t)	(0.0022)	(0.0020)	(0.0013)
N	904,780	904,780	904,780
Adj. R-sq.	0.6397	0.0293	0.8001
Controls	yes	yes	yes
year*industry fe	yes	yes	yes
firm fe	yes	yes	yes
year*main bank fe	yes	yes	yes

4.2.1.4. *Effect of government-controlled banks*

The government often introduces a special lending program through government-controlled banks (Development Bank of Japan (DBJ), Japan Finance Corporation (JFC), and Shoko Chukin Bank) for firms located in disaster-hit areas. To see their impact, we introduce the dummy variable, *government bank*, indicating that a firm borrows a loan from these policy banks in each current year, and the interaction term of it with *damage10* or *hit_quake*, into the baseline regression. The regressions so far use the dataset excluding firms whose largest lender is a government-controlled bank since financial variables for these banks are not fully available. To avoid the resulting bias, we introduce main-bank times year fixed effect in place of main bank characteristics.

Table 10 shows the results. Coefficients of the dummy variables indicating a 10-percentile flood or an earthquake and their lags are similar to the baseline regression in Table 7. The interaction term of the flood dummy, *damage10*, and the government bank dummy does not have any statistically significant coefficients. Thus, the impact of government banks is not visible in the case of floods. On the other hand, the interaction term of an earthquake dummy and the government bank has a positive and statistically significant coefficient for the long-term loan in the year of an earthquake. This is consistent with the regulation that DBJ and JFC are allowed to provide only long-term loans. The impact of government-controlled banks is visible only for earthquakes.

4.2.2. *Trade credit and cash holding after a flood*

4.2.2.1. *Baseline*

Table 11 shows the baseline result of the regression with respect to trade credit and cash holding. Trade credit is defined as payable minus receivable, i.e., net short-term borrowing from other firms. Cash holding is the ratio of cash and cash equivalent over total asset except for cash.

Table 11. Trade credit and cash holding after a flood: Baseline

(Notes) Estimated coefficients are listed. Dependent variable is indicated at the top of each column. Constant is omitted from the report. Firm and sector-year two-way clustered standard errors in parentheses. Constant term is omitted. *** p<0.01, ** p<0.05, * p<0.1 (two-sided).

	(1)	**(2)**	**(3)**	**(4)**
Variables	**Δtrade credit/asset**	**Δpayable/asset**	**Δreceivable/asset**	**Δcash hold**
damage10(t)	0.0001	0.0014***	0.0013*	0.0061***
	(0.0005)	(0.0005)	(0.0007)	(0.0017)
damage10(t-1)	0.0014***	-0.0001	-0.0015***	0.0033**
	(0.0005)	(0.0003)	(0.0005)	(0.0015)
damage10(t-2)	0.0005	-0.0003	-0.0008	-0.0033**
	(0.0006)	(0.0006)	(0.0005)	(0.0014)
hit_quake(t)	-0.0024	0.0018	0.0042	0.0145***
	(0.0022)	(0.0017)	(0.0035)	(0.0031)
hit_quake(t-1)	0.0045*	0.0042***	-0.0003	0.0159**
	(0.0024)	(0.0012)	(0.0020)	(0.0062)
hit_quake(t-2)	0.0018*	-0.0038***	-0.0055***	-0.0038
	(0.0010)	(0.0009)	(0.0015)	(0.0032)
leverage(t-1)	-0.0321***	-0.0531***	-0.0211***	-0.0166***
	(0.0032)	(0.0037)	(0.0037)	(0.0052)
score(t-1)	-0.0003***	-0.0018***	-0.0014***	-0.0035***
	(0.0001)	(0.0001)	(0.0001)	(0.0005)
Δsales/asset(t-1)	-0.0030***	-0.0036***	-0.0006	0.0091***
	(0.0006)	(0.0005)	(0.0009)	(0.0016)
Δsales/asset(t)	-0.0125***	0.0304***	0.0429***	0.1093***
	(0.0008)	(0.0020)	(0.0020)	(0.0049)
MB exposure1(t)	-0.0025	-0.0047***	-0.0022	0.0020
	(0.0018)	(0.0017)	(0.0022)	(0.0039)
MB exposure_quake(t)	0.0027	0.0070**	0.0043	-0.0045
	(0.0024)	(0.0027)	(0.0037)	(0.0063)
MB in quake(t)	0.0025	-0.0029*	-0.0054*	-0.0038
	(0.0016)	(0.0017)	(0.0029)	(0.0029)
MB in 10pc flood(t)	0.0002	0.0020***	0.0017**	0.0012
	(0.0008)	(0.0004)	(0.0008)	(0.0012)
MB liquidity ratio(t)	-0.0000	-0.0000	-0.0000	0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.0001)
MB leverage ratio(t)	0.0004	-0.0009***	-0.0013***	-0.0015*
	(0.0003)	(0.0003)	(0.0005)	(0.0008)

N	873,864	873,864	873,864	873,864
Adj. R-sq.	-0.1089	-0.0708	-0.0756	0.0108
year*industry fe	yes	yes	yes	yes
firm fe	yes	yes	yes	yes

Both payable and receivable increase significantly in the year of a flood. The cash holding also increases significantly. Firms hit by a flood stop paying cash, which results in an increase in payables for these firms and the increase in receivables for other firms. In addition, the increase in payables may lead to a higher level of cash holding. The receivables are cashed soon in the next year of a flood, possibly discounted by banks. Only payables remain at a higher level in this year, which contributes to the higher level of cash holding. After an earthquake, cash holding also tends to increase, while trade credit increases with some time lag.

The estimated coefficients of control variables indicate that firms with higher leverage or those with higher credit scores depend less on trade credit. The increase in sales in the current year increases both payables and receivables. The increase in sales also leads to an increase in cash holding, which indicates that firms recognize some constraints in borrowing from a bank (Almeida et al. 2004). A notable coefficient among the main-bank characteristics is that of the leverage ratio, or capital ratio. Firms with better capitalized main bank depend less on trade credit and hold less cash.

4.2.2.2. Damaged and not damaged

To see the difference between those directly damaged and those not, we include the dummy variable, *tangible loss*, which equals one if a firm report non-zero loss on tangible assets, and the interaction term of it and *damage10*.

Table 12. Trade credit and cash holding after a flood: Damaged and Not Damaged

(Notes) Estimated coefficients are listed. Dependent variable is indicated at the top of each column. Control variables include those in Table 11 and *tangible loss* (t, t-1, t-2). Firm and sector-year two-way clustered s.e. in parentheses. Constant is omitted. *** p<0.01, ** p<0.05, * p<0.1 (two-sided).

	(1)	(2)	(3)	(4)
Variables	**Δtrade credit/asset**	**Δpayable/asset**	**Δreceivable/asset**	**Δcash hold**
damage10(t)	-0.0003	0.0012**	0.0015*	0.0061***
	(0.0006)	(0.0005)	(0.0008)	(0.0020)
damage10(t-1)	0.0012**	-0.0000	-0.0013**	0.0032*
	(0.0006)	(0.0004)	(0.0006)	(0.0016)
damage10(t-2)	0.0005	-0.0002	-0.0007	-0.0035**
	(0.0007)	(0.0007)	(0.0006)	(0.0017)
damage10*tangible loss(t)	0.0021**	0.0008	-0.0013	0.0002
	(0.0009)	(0.0008)	(0.0011)	(0.0028)
damage10*tangible loss(t-1)	0.0008	-0.0002	-0.0009	0.0003
	(0.0010)	(0.0009)	(0.0011)	(0.0021)
damage10*tangible loss(t-2)	0.0002	-0.0001	-0.0003	0.0006
	(0.0012)	(0.0011)	(0.0015)	(0.0024)
hit_quake(t)	-0.0029	0.0019	0.0049	0.0150***
	(0.0022)	(0.0016)	(0.0035)	(0.0038)
hit_quake(t-1)	0.0051*	0.0050***	-0.0001	0.0171**
	(0.0026)	(0.0014)	(0.0021)	(0.0071)
hit_quake(t-2)	0.0018	-0.0042***	-0.0060***	-0.0032
	(0.0015)	(0.0009)	(0.0018)	(0.0037)
hit_quake*tangible loss(t)	0.0022	-0.0003	-0.0026	-0.0020
	(0.0018)	(0.0013)	(0.0021)	(0.0040)
hit_quake*tangible loss(t-1)	-0.0020	-0.0031*	-0.0011	-0.0043
	(0.0017)	(0.0017)	(0.0016)	(0.0049)
hit_quake*tangible loss(t-2)	-0.0000	0.0018	0.0018	-0.0025
	(0.0024)	(0.0014)	(0.0022)	(0.0031)
N	873,864	873,864	873,864	873,864
Adj. R-sq.	-0.1089	-0.0708	-0.0756	0.0108
Controls	yes	yes	yes	yes
year*industry fe	yes	yes	yes	yes
firm fe	yes	yes	yes	yes

The result is summarized in Table 12. The coefficients of *damage10* and its lags are the same as the previous table. The stark difference from the previous result is found in the coefficient of 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 policy, those that are physically damaged by flood rely more on trade credit (positive and significant coefficient of *damage10*tangible loss(t)* in Column (1) on trade credit). We do not find such behaviors in an earthquake.

4.2.2.3. Impact of damaged suppliers and customers

To see the effect of the damage on suppliers and customers, we introduce the interaction term of *damage10* and the ratio of corporate customers or the ratio of suppliers who report non-zero losses on their tangible asset into the model of Table 12. Table 13 is the summary of this regression. The interaction term of damage10 and the damaged customer ratio have a positive and significant coefficient in the regressions of payable and receivable. This implies that a firm increases receivable when their customers are damaged by a flood. They also increase payables to fill in the resulting gap in cash. The interaction term of *damage10* and the damaged supplier ratio also have a positive and significant coefficient in these regressions.

Table 13. Trade credit and cash holding after a flood: Damage on Customers/Suppliers

(Notes) Estimated coefficients are listed. Dependent variable is indicated at the top of each column. Control variables include those in Table 11 and *tangible loss* (t,t-1,t-2). Firm and sector-year two-way clustered s.e. in parentheses. Constant is omitted. *** p<0.01, ** p<0.05, * p<0.1 (two-sided).

	(1)	**(2)**	**(3)**	**(4)**
Variables	**Δtrade credit/asset**	**Δpayable/asset**	**Δreceivable/asset**	**Δcash hold**
damage10(t)	-0.0001	0.0008	0.0008	0.0059***
	(0.0006)	(0.0006)	(0.0008)	(0.0022)
damage10(t-1)	0.0009	-0.0001	-0.0009	0.0028
	(0.0006)	(0.0004)	(0.0006)	(0.0017)
damage10(t-2)	0.0003	-0.0003	-0.0006	-0.0036**
	(0.0007)	(0.0006)	(0.0006)	(0.0015)
damage10*tangible loss(t)	0.0021**	0.0008	-0.0014	-0.0002
	(0.0009)	(0.0008)	(0.0011)	(0.0029)
damage10*tangible loss(t-1)	0.0008	-0.0002	-0.0010	0.0002
	(0.0010)	(0.0009)	(0.0011)	(0.0023)
damage10*tangible loss(t-2)	0.0004	-0.0002	-0.0006	0.0008
	(0.0012)	(0.0010)	(0.0016)	(0.0023)
damage10(t)	0.0003	0.0035**	0.0032**	0.0060*
*damaged customer ratio(t)	(0.0015)	(0.0016)	(0.0013)	(0.0032)
damage10(t-1)	0.0002	-0.0004	-0.0005	0.0027
*damaged customer ratio(t-1)	(0.0014)	(0.0012)	(0.0020)	(0.0051)
damage10(t-2)	-0.0002	0.0018	0.0020	-0.0057
*damaged customer ratio(t-2)	(0.0015)	(0.0012)	(0.0016)	(0.0041)
damage10(t)	-0.0014	0.0038***	0.0051***	0.0011
*damaged supplier ratio(t)	(0.0016)	(0.0014)	(0.0017)	(0.0043)
damage10(t-1)	0.0019	0.0005	-0.0014	0.0066**
*damaged supplier ratio(t-1)	(0.0015)	(0.0012)	(0.0019)	(0.0027)
damage10(t-2)	0.0003	-0.0005	-0.0008	0.0005
*damaged supplier ratio(t-2)	(0.0015)	(0.0012)	(0.0019)	(0.0034)
N	840,215	840,215	840,215	840,215
Adj. R-sq.	-0.1087	-0.0678	-0.0736	0.0098
Controls	yes	yes	yes	yes
year*industry fe	yes	yes	yes	yes
firm fe	yes	yes	yes	yes

4.3. Investment and employment after flood disaster

4.3.1. Baseline

We next examine the investment and employment of firms headquartered in flood municipalities and report results in Table 14. While we observe an increase in the investment in the year of the flood, the impact of floods on employment is not eminent until two years after the flood. This is evidenced by the positive and significant coefficient of *damage10* in Column (1), and positive and significant coefficient of *Damage10(t-2)* in Column (2). Meanwhile, *hit_quake(t-1)* and *hit_quake(t-2)* are significant in Column (1) but not in Column (2) suggesting that investment on fixed asset increases in the next two years following an earthquake but employment does not seem to change following an earthquake.

The coefficients of control variables also show interesting results. The negative and highly statistically significant coefficients of leverage in both investment and employment indicate the significant effect of the debt overhang (Myers 1977), i.e., higher indebtedness impairs firm growth. Higher credit score increases investment but reduces employment. Firms increase investment and employment in response to sales growth to some extent. Firms increase their investment when the operating cash flow per tangible asset is larger, and when tangible asset is smaller relative to cash flow (ec_tangible). This patter is the same for employment.

Table 14. Investment and Employment after a Flood (baseline)

(Notes) Estimated coefficients are listed. Dependent variable is indicated at the top of each column. Firm and sector-year two-way clustered standard errors in parentheses. Constant term is omitted from the report. *** p<0.01, ** p<0.05, * p<0.1 (two-sided).

Variables	(1) I/K	(2) Δemployee
damage10(t)	0.0008***	0.0156
	(0.0003)	(0.0109)
damage10(t-1)	0.0004	0.0147
	(0.0003)	(0.0105)
damage10(t-2)	0.0002	0.0216*
	(0.0003)	(0.0125)
hit_quake(t)	0.0007	0.0177
	(0.0006)	(0.0314)
hit_quake(t-1)	0.0038***	-0.0042
	(0.0006)	(0.0217)
hit_quake(t-2)	0.0027***	-0.0084
	(0.0006)	(0.0228)
leverage(t-1)	-0.0148***	-0.2741***
	(0.0010)	(0.0333)
score(t-1)	0.0008***	-0.0083***
	(0.0001)	(0.0027)
MB exposure1(t)	-0.0013	0.0042
	(0.0012)	(0.0423)
MB exposure_quake(t)	-0.0008	0.0560
	(0.0012)	(0.0688)
MB HQ hit by quake(t)	0.0013**	-0.0452*
	(0.0005)	(0.0255)
MB HQ hit by 1pc flood(t)	-0.0000	-0.0140
	(0.0003)	(0.0126)
MB liquidity ratio(t)	0.0000	0.0009
	(0.0000)	(0.0010)
MB leverage ratio(t)	-0.0002	-0.0013
	(0.0002)	(0.0071)
sales growth rate(t)	0.0056***	1.0612***
	(0.0005)	(0.0808)
(sales growth rate(t))^2	-0.0023***	-0.5522***
	(0.0005)	(0.0647)

cash flow/tangible asset(t)	0.0004***	
	(0.0001)	
cash flow/tangible asset(t-1)	0.0003***	
	(0.0000)	
ec_tangible(t-1)	0.0001***	
	(0.0000)	
cash flow/#employees(t)		0.0329***
		(0.0064)
cash flow/#employees(t-1)		-0.0037
		(0.0071)
ec_employee(t-1)		0.0517***
		(0.0020)
Observations	873,864	873,864
Adjusted R-squared	0.1108	0.0737
year*industry fe	yes	yes
firm fe	yes	yes

4.3.2.Damaged and not damaged

We further examine the heterogeneity in the impact of floods on investment and employment between physically damaged firms and the others in flood locations. Similar to the previous analyses, we include a dummy variable, *tangible loss*, and its interaction with *damage10* and report our results in Table 15. Across the two columns of Table 15, the coefficients of *damage10* load consistently with those reported in the previous table but interestingly, behave differently when compared with those of *damage10*tangible loss*. It indicates that our results drawn from Table 14 are driven by those located in the flood area but not physically damaged by flood. The positive and significant coefficients of *damage10* and negative coefficient of *damage10_loss* in Column (1) suggest that while non-damaged firms in flood areas increase investment in the flood year and the next two years, firms that are physically damaged by flood reduce their investment during the two years after flood.

The positive and significant coefficient of *damage10(t-2)* in Column (2) becomes negative and insignificant for the physically damaged firms. This implies that two years after the flood, non-damaged firms in the flood areas expand their business by attracting more employees while those that are damaged by floods do not exhibit any change in their workforce size.

When examining the investment and employment policies of firms following an earthquake, we find that both damaged and non-damaged firms increase their investment. The investment increase in the damaged one happens in the year of earthquake while that in the non-damaged ones happens during the two years after the earthquake. Interestingly, there is an increase in the employees of non-damaged firms but a decrease in the employees of damaged firms in the earthquake year.

These difference between the responses to a flood and an earthquake can come from the difference in the frequency of these types of disasters. Floods are more often repeated, even every year. Firms that learn the flood risk of their site might avoid rebuilding in the same site and search for other location or opportunity.

Table 15. Investment and Employment after a Flood: Damaged and Not Damaged

(Notes) Estimated coefficients are listed. Dependent variable is indicated at the top of each column. Control variables include those in Table 14 and *tangible loss* (t,t-1,t-2). Firm and sector-year two-way clustered s.e. in parentheses. Constant term is omitted . *** p<0.01, ** p<0.05, * p<0.1 (two-sided).

	(1)	(2)
Variables	**I/K**	**Δemployee**
damage10(t)	0.0007**	0.0038
	(0.0003)	(0.0125)
damage10(t-1)	0.0006*	0.0159
	(0.0004)	(0.0155)
damage10(t-2)	0.0006*	0.0426***
	(0.0003)	(0.0153)
damage10*tangible loss(t)	-0.0009	-0.0480
	(0.0009)	(0.0471)
damage10*tangible loss(t-1)	-0.0019**	-0.0598

	(0.0008)	(0.0411)
damage10*tangible loss(t-2)	-0.0017**	-0.0455
	(0.0008)	(0.0499)
hit_quake(t)	0.0006	0.0762**
	(0.0006)	(0.0327)
hit_quake(t-1)	0.0037***	-0.0101
	(0.0007)	(0.0286)
hit_quake(t-2)	0.0026***	-0.0287
	(0.0007)	(0.0243)
hit_quake*tangible loss(t)	0.0007	-0.1734**
	(0.0008)	(0.0870)
hit_quake*tangible loss(t-1)	0.0003	-0.0197
	(0.0008)	(0.0817)
hit_quake*tangible loss(t-2)	0.0007	-0.0183
	(0.0009)	(0.0684)
N	873,864	873,864
Adj. R-sq.	0.1110	0.0738
Controls	yes	yes
year*industry fe	yes	yes
firm fe	yes	yes

4.3.3.Effect of government-controlled banks

We further explore the role of government-controlled banks in stimulating corporate investment and employment levels in the flood area. We perform tests that are similar to the previous ones by introducing a dummy variable, *government bank*, and its interaction term with *damage10* or *hit_quake*. Our results are summarized in Table 16.

Among all interaction terms of *damage10* or *hit_quake* with *government bank*, we find positive and significant coefficients of *damage10(t-1)*government bank(t), hit_quake(t-1)*government bank(t)* in Column (1) and *hit_quake(t-2)*government bank(t)* in Column (2). It suggests that firms that borrow from government-controlled banks, on average, experience higher investment one year after disasters (i.e., flood and earthquake). On the other hand, the impact of government-controlled banks is only visible two years following earthquakes but not floods. This result reflects the massive public lending program for the recovery from devastating earthquakes through these banks.

Table 16. Investment and Employment after a Flood: Government-Controlled Banks

(Notes) Estimated coefficients are listed. Dependent variable is indicated at the top of each column. The set of control variables is those in Table 10. Firm, sector-year, and bank-year three-way clustered standard errors in parentheses. Constant term is omitted. *** p<0.01, ** p<0.05, * p<0.1 (two-sided).

Variables	(1) I/K	(2) Δemployee
damage10(t)	0.0009***	0.0106
	(0.0003)	(0.0117)
damage10(t-1)	0.0005*	0.0012
	(0.0003)	(0.0120)
damage10(t-2)	0.0003	-0.0033
	(0.0003)	(0.0137)
damage10(t)	0.0001	-0.0200
*government bank(t)	(0.0007)	(0.0272)
damage10(t-1)	0.0001	-0.0293
*government bank(t)	(0.0007)	(0.0296)
damage10(t-2)	-0.0003	0.0505*
*government bank(t)	(0.0005)	(0.0303)
hit_quake(t)	0.0013*	-0.0320
	(0.0007)	(0.0243)
hit_quake(t-1)	0.0020***	-0.0565
	(0.0006)	(0.0394)
hit_quake(t-2)	0.0009	-0.0312
	(0.0006)	(0.0448)
hit_quake(t)	0.0009	0.0017
*government bank(t)	(0.0012)	(0.0377)
hit_quake(t-1)	0.0025***	0.0787
*government bank(t)	(0.0008)	(0.0690)
hit_quake(t-2)	0.0005	-0.0418
*government bank(t)	(0.0013)	(0.0514)
N	904,780	904,780
Adj. R-sq.	0.1095	0.0721
Controls	yes	yes
year*industry fe	yes	yes
firm fe	yes	yes
year*main bank fe	yes	yes

4.4. Robustness checks

We conduct a battery of analyses for robustness checks. The results are provided in the appendix. First, we conduct the pre-trend analysis to ensure that the impact of disasters is exogenous. In particular, we re-estimate all of our previous regressions adding the one-year-lead dummy for floods and one-year-lead dummy for earthquakes. The results so far are all intact against this modification.

Second, as our statistics in Table 2 reveal the over-presence of the construction sector in our sample, we re-run our regressions in two different sub-samples, i.e., the construction sector and the other sectors. The results regarding loans and investments are statistically significant but weaker in other sectors than in the construction sector. However, the result that those physically damaged firms rely more on trade credit is stronger in the other sectors than in the construction sector.

Finally, we restrict our sample to include only firms with at least ten years of observations to reduce the noise from firms less frequently monitored by TSR. The results we have got so far are more statistically significant in this subsample.

5. Bank-level analysis

In this section, we study how exposure to floods affects bank performance, i.e., bank loans, deposits, liquidity, and non-performing loans. We estimate the following regression equation:

$$y_{it} = \beta_0 + \beta_1 exposure10_{it} + \beta_2 exposure10_{it-1} + \beta_3 exposure10_{it-2} + \beta_4' X_{it} + \eta_t + \mu_i + \epsilon_{it}, \quad (2)$$

where y_{it} indicates bank performance measures, such as changes in total loans (Δln_loan), deposits ($\Delta ln\_deposit$), liquidity ratio ($\Delta liquidity$), non-performing loan ratio ($\Delta non\text{-}performing\ loan$); i indicates bank; t indicates year. $exposure10_{it}$ is the ratio of SME borrowers of bank i located in a 10-percentile flood area in year t. X_{it} is the vector of control variables, and β_4 is the vector of the coefficients of them. η_t and μ_i indicate the year and bank fixed effect, respectively. The regression results of Equation (2) are presented in Column (1), Table 17.

Table 17. Bank-level analyses

(Notes) Estimated coefficients from the bank-level data are listed. Dependent variable is indicated at the top of each column. Bank and year two-way clustered standard errors in parentheses. Constant is omitted. *** p<0.01, ** p<0.05, * p<0.1 (two-sided).

Variables	(1) Δln_loan	(2) Δln_deposit	(3) Δliquidity ratio	(4) ΔNPL ratio
exposure10(t)	-0.003	-0.002	-0.459*	-0.224
	(0.004)	(0.007)	(0.234)	(0.154)
exposure10(t-1)	0.009	0.004	-0.383	-0.281
	(0.009)	(0.005)	(0.448)	(0.185)
exposure10(t-2)	0.001	-0.011***	-1.118**	0.010
	(0.008)	(0.003)	(0.391)	(0.072)
B exposure_quake(t)	-0.009	0.020***	1.268*	-0.019
	(0.008)	(0.006)	(0.698)	(0.235)
B exposure_quake(t-1)	-0.017	-0.004	-0.392	-0.908
	(0.011)	(0.016)	(0.683)	(0.679)
B exposure_quake(t-2)	0.001	0.014***	0.244	-0.506**
	(0.010)	(0.004)	(0.343)	(0.221)
B HQ hit by 10pc flood (t)	-0.001	0.004	0.286*	-0.025
	(0.002)	(0.003)	(0.144)	(0.067)
B HQ hit by 10pc flood (t-1)	-0.002	-0.000	0.240	0.118
	(0.002)	(0.003)	(0.272)	(0.074)
B HQ hit by 10pc flood (t-2)	0.000	0.005**	0.429	-0.037
	(0.005)	(0.002)	(0.237)	(0.072)
B HQ hit by quake(t)	0.004	-0.008	-0.076	0.107
	(0.008)	(0.005)	(0.317)	(0.113)
B HQ hit by quake(t-1)	0.021**	0.021***	1.243**	0.681*
	(0.007)	(0.006)	(0.440)	(0.355)
B HQ hit by quake(t-2)	0.012*	0.012	0.397	0.359
	(0.006)	(0.009)	(0.289)	(0.300)
ROA(t-1)	0.008**	0.001		
	(0.003)	(0.004)		
liquidity ratio(t-1)	0.002***	-0.001**		
	(0.000)	(0.000)		
leverage ratio(t-1)	0.002	0.001		
	(0.001)	(0.002)		

N	4,054	4,054	4,054	4,050
Adj. R-sq.	0.339	0.249	0.196	0.057
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

As shown in Column (1), Table 17, β_1, β_2, and β_3 are all statistically insignificant at conventional levels, suggesting that current and lagged exposures to floods do not have a significant effect on bank lending. Similarly, we find no significant association between exposure to earthquake and the change in total loan. The coefficients of $B\ HQ\ hit\ by\ quake_{t-k}$, a dummy variable indicating that bank headquarter is located in an earthquake-hit municipality at time $t-k$, is positive and statistically significant at the 5% and 10% level when k equals 1 and 2, respectively, suggesting that the bank loan growth increases with one or two-year lag after the bank's headquarter experiences an earthquake. Consistent with the existing literature, a bank increases lending when it is more profitable and liquid. Specifically, the coefficient of ROA_{t-1} is positive and statistically significant at the 5% level, and the coefficient of liquidity ratio is positive and significant at the 1% significance level. We, however, do not find a significant association between the lagged measure of leverage and bank lending as suggested in the literature.

Column (2), Table 17, reports regression results of the change in bank deposits, i.e., $\Delta ln\_deposit_{i,t}$. Overall, bank deposits do not change significantly in response to flood exposures. Only the coefficient of $exposure10_{t-2}$ is negative at -0.011 and statistically significant at the 1% level in Column (2), while the coefficients of $exposure10_t$ and $exposure10_{t-1}$ are both statistically insignificant, and their signs are mixed. On the other hand, bank deposits increase significantly in response to high levels of exposure to earthquakes, i.e., the coefficients of $B\ exposure\_quake_t$ and $B\ exposure\_quake_{t-2}$ are positive and statistically significant at the 1% level. This suggests the impact of the massive government subsidies for firms and households after experiencing an earthquake. Column (2) also shows a negative and statistically significant effect of lagged liquidity ratio on the deposit growth. In addition, the deposit growth decreases when the bank's headquarter experiences an earthquake; however, it recovers in the following year. The coefficient of $B\ \ HQ\ hit\ by\ quake_{\ t-1}$ is positive and statistically significant at the 1% level.

The analysis of liquidity in Column (3), Table 17, reveals that the liquidity ratio decreases after high exposures to floods. In Column (4), we find that exposures to floods have no statistically significant influence on banks' non-performing-loan ratio. The above results are qualitatively similar when we estimate the above equations with a subsample of shinkin banks (Table 18).

6. Policy implications

Our findings have several policy implications. First, floods reallocate loans, capital and employment from firms physically damaged to nearby firms without physical damages. This seemingly cruel process contributes to the relocation of resources to safer areas. Public subsidies and recovery lending programs should be designed to promote this process rather than a literal restoration. Second, trade credit plays a crucial role in absorbing a shock of disasters through a supply-chain network. This suggests that an increase in loans to a hub firm in a network can mitigate a liquidity shortage at firms connected to damaged ones through trade credits. It can be an efficient strategy for regional financial institutions and government-controlled banks to identify such hub firms and inject loans or capital into them. Third, we find that sales and loans increase after a flood, particularly in the construction sector. This result reflects the fact that the damage to public infrastructures often accounts for a larger part of flood damage, and so public works tend to increase sharply after a flood. This implies that we have to be more concerned about the impact of floods on the government deficit, although this point is out of the scope of this study.

Table 18. Shinkin banks

(Notes) Estimated coefficients from the bank-level data including shinkin banks only are listed. Dependent variable is indicated at the top of each column. Bank and year two-way clustered s.e. in parentheses. Constant is omitted. *** p<0.01, ** p<0.05, * p<0.1 (two-sided).

Variables	(1) Δln_loan	(2) Δln_deposit	(3) Δliquidity ratio	(4) ΔNPL ratio
exposure10(t)	-0.006	-0.003	-0.018	-0.178
	(0.006)	(0.007)	(0.090)	(0.167)
exposure10(t-1)	0.002	0.003	-0.057	-0.460*
	(0.008)	(0.004)	(0.402)	(0.248)
exposure10(t-2)	-0.001	-0.008*	-0.644	0.023
	(0.011)	(0.004)	(0.458)	(0.087)
B exposure_quake(t)	-0.016	0.022**	1.603**	0.157
	(0.010)	(0.008)	(0.584)	(0.245)
B exposure_quake(t-1)	-0.019	-0.024	-2.001**	-0.897
	(0.013)	(0.018)	(0.741)	(1.014)
B exposure_quake(t-2)	-0.014**	0.009	0.294	-0.452
	(0.005)	(0.009)	(0.404)	(0.369)
B HQ hit by 10pc flood (t)	0.001	0.002	0.053	-0.048
	(0.002)	(0.003)	(0.112)	(0.087)
B HQ hit by 10pc flood (t-1)	0.004	0.001	-0.111	0.227*
	(0.003)	(0.004)	(0.228)	(0.125)
B HQ hit by 10pc flood (t-2)	0.005	0.003	0.057	-0.018
	(0.005)	(0.003)	(0.305)	(0.112)
B HQ hit by quake(t)	0.006	-0.013**	-0.466	0.030
	(0.009)	(0.005)	(0.342)	(0.137)
B HQ hit by quake(t-1)	0.018	0.022**	1.826**	0.723
	(0.011)	(0.009)	(0.604)	(0.600)
B HQ hit by quake(t-2)	0.013	0.028**	1.466***	0.469
	(0.008)	(0.012)	(0.436)	(0.542)
ROA(t-1)	0.009***	0.001		
	(0.002)	(0.006)		
liquidity ratio(t-1)	0.001***	-0.001**		
	(0.000)	(0.001)		
leverage ratio(t-1)	0.002	0.000		
	(0.002)	(0.003)		
N	2,845	2,845	2,845	2,845
Adj. R-sq.	0.326	0.275	0.217	0.066
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

7. Conclusion

We examine the financial impact of severe floods in Japan during the 2010-2020 period. We conduct empirical analyses at both corporate and bank levels using comprehensive datasets of about 100 thousand small and medium-sized enterprises (SMEs), and about 380 banks in Japan. At 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 et al. 2017, Koetter et al. 2020). We observe a heterogenous impact of flood on corporate policies within flood-damaged areas. Firms that are located in the flood area but not physically damaged by flood increase bank loans, especially long-term loans, whereas the opposite response is found in the group of physically damaged by flood. With less reliance on bank loans, the latter firms rely more on trade credit, which mostly comes from the tightening trade credit policy leading to the reduction in receivables. We also find that following floods, the non-damaged firms increase their investment and employees but the damaged ones experience a significant drop in investment and no statistical change in employee.

A further analysis conducted at the bank level, where no significant impact of floods is found, suggests the potential credit reallocation by banks within the disaster-hit areas. Besides, we document the role of government-controlled banks in increasing long-term loans, investment, and employees following an earthquake. While we also find evidence that firms that borrow from government-controlled banks increase investment following a flood, the role of government-controlled banks in long-term lending and job creation in a flood-hit area is not visible.

Severe floods forcibly reallocate economic resources from vulnerable areas to safer areas. The forecasted increase in the frequency and magnitude of floods implies a wider range of geographical resource reallocation in the near future.

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