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Quantitative Analysis of the Impact of Floods on Firms' Financial Conditions

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Abstract

This paper quantitatively analyzes the impact of floods on firms' financial conditions from the perspective of contributing to the accumulation of basic research on climate-related financial risks, while taking into account the risk characteristics of Japan, where floods are one of the most common natural disasters. Since the damage from most floods tends to concentrate in a confined geographical area, a precise evaluation of their financial impact requires an assessment of sufficiently granular data, which is a challenge for the existing studies. In order to address that challenge, this paper combines *Flood Statistics*, which records almost all flood damage that has occurred in Japan at the municipality level, with firm-level financial data, and this makes it possible for us to analyze the impact of floods on firms' financial conditions with greater accuracy and granularity in comparison with previous studies.

The three main conclusions of this paper are as follows. First, flood damage has a negative impact on the ratio of profit to sales, especially in the manufacturing industry. Second, the impact of floods on this ratio lessens in the short term. And third, the negative impact tends to be greater for firms located in municipalities that experienced floods with less frequency. Financial institutions need to pay close attention to the possibility that floods may cause more deterioration in firms' financial conditions than ever before as a consequence of climate change, and thus endeavor to enhance their risk management framework, bearing in mind that risk characteristics may vary depending on lenders' characteristics.

JEL *classification*: C21; D22; Q54; R10

Keywords : Climate change; Natural disaster; Corporate finance; Physical risk; Financial stability

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1. Introduction

In recent years, against the backdrop, an increasingly heated debate has emerged worldwide over the impact of climate change and countermeasures. According to research jointly conducted by the Ministry of Education, Culture, Sports, Science and Technology (MEXT) and the Japan Meteorological Agency (JMA), the most notable example of climate change is that rainfall in Japan has become more extreme, with the frequency of heavy rains, including short-duration heavy rains, increasing significantly (MEXT and JMA [2020]).[1] In Japan, flood-related disasters such as typhoons, floods, and landslides account for more than 70% of all natural disasters (Figure 1)[2], due in part to the geographical conditions of small inhabitable areas and steep river slopes. Under these circumstances, the amount of damage caused by floods per unit area has been on the rise for the past 10 years (Figure 2), in line with the increasing extremes in rainfall.[3]

This trend in Japan is likely to intensify in the future as a consequence of climate change. The Intergovernmental Panel on Climate Change (IPCC) shows climate projections simulated under four greenhouse gas emission scenarios, including the case where measures are taken to achieve the international agreement on greenhouse gas emissions, which is equivalent to the "RCP2.6 scenario," and the case where no additional measures are taken, which is equivalent to the "RCP8.5 scenario." It is pointed out that the global average temperature will rise by the end of this century under all scenarios (IPCC [2013]). The MEXT and the JMA jointly conducted simulations assuming the RCP2.6 and the RCP8.5 scenarios, and predicted that the annual average temperature in Japan would rise by about 1.4 to 4.5 degrees Celsius and that the frequency of heavy rainfall would significantly increase by the end of the century (MEXT and JMA [2020]). The Ministry of Land, Infrastructure, Transport and Tourism (MLIT) has

[1] In general, a temperature rise leads to a decrease in frequency of precipitation, while the volume of each precipitation event tends to rise, due to an increase in the amount of water vapor in the air. In fact, upper-air observation data collected by the JMA demonstrates an upward trend in the specific humidity ratio, which refers to the mass of water vapor in a unit mass of moist air at a height of about 1,500 meters. Another data set from the JMA reveals that the frequency of heavy rainfalls with precipitation of ≥ 50 mm per hour for the last 10 years, from 2011 to 2020, has increased about 1.5 times compared with the 10 years from 1976 to 1985. For rainfalls with precipitation of ≥ 80 mm per hour, the frequency rises further to 1.9 times.

[2] For the global mass disaster database, researchers broadly use the Emergency Events Database (EM-DAT) provided by the Centre for Research on the Epidemiology of Disasters (CRED) within the Université catholique de Louvain. The EM-DAT includes global disasters that occurred in more than 220 countries and areas, conforming to at least one of following criteria: (1) 10 or more people dead, (2) 100 or more people affected, (3) the declaration of a state of emergency, and (4) a call for international assistance. According to the EM-DAT, Japan ranks seventh in terms of the number of global natural disaster events for the last 40 years.

[3] Development of residential lands in high-risk flood areas may be another factor for this trend. The ratio of residential populations within estimated flood inundation areas in Japan to the whole population calculated by Hada and Maeda [2020] rose consistently from 1995 (26.8%) to 2015 (28%).

estimated that, under these two scenarios, the frequency of floods will increase from two to four times (MLIT [2021]). Thus, there is growing concern about the secular increase in flood risk in Japan as a result of climate change

Financial authorities as well as financial institutions all over the world have urgently identified possible significant risks caused by climate change to the financial soundness and business environment of financial institutions and, ultimately, to the stability of the financial system. Such risks, generally referred to as "climate-related financial risks," have provoked intense discussions on their spillover channels and regarding their measurement methods.[4] According to these discussions, climate-related financial risks can be broadly categorized into two types: physical and transition risks. Physical risks refer to the possibility of economic losses to companies and households caused by extreme weather events due to climate change, and transition risks relate to changes in policies, technologies, and consumer preferences in response to the shift toward a low-carbon economy, as well as the possibility that these changes might cause economic losses. Flooding is recognized as one of the most typical manifestations of physical risk because it can adversely affect the soundness of financial institutions by reducing the repayment capacity of affected borrowers (e.g., companies and households). As mentioned earlier, floods account for more than 70% of all natural disasters that occur in Japan, and there is concern that the risk of floods will continue to increase as a consequence of climate change. In these circumstances, some Japanese financial institutions have implemented scenario analysis of physical risks and tried to estimate credit costs associated with floods.[5]

Analysis of climate-related financial risks has just begun worldwide, and is in the phase of accumulating new knowledge with the goal of accurately understanding and managing their characteristics. In this context, this paper quantitatively analyzes the impact of floods on firms' financial conditions from the perspective of contributing to the accumulation of basic research on climate-related financial risks while taking into account the risk characteristics of Japan, where floods are one of the most common natural disasters.

The damage from most floods tends to concentrate in a confined geographical area. Especially in Japan, where inundation areas are on a downward trend owing to various flood control measures, as seen in Figure 2, floods are recognized as extremely localized phenomena. Therefore, as will be described later, a precise evaluation of their financial impact requires an assessment of sufficiently granular data. In this regard, in Japan there is the MLIT's *Flood*

[4] The Bank of Japan joined the Network for Greening the Financial System (NGFS) as a member in 2019, which is a voluntary group of central banks and supervisors willing to exchange experiences and discuss the issues regarding climate-related financial risks, in order to make a further contribution to the international discussion. For the international developments of issues around climate-related financial risks and a survey of previous studies, see Shibakawa, Naka, and Kobayashi [2020] and Furukawa et al. [2020].

[5] For example, three major banks in Japan have published the estimation results of scenario analysis on the impact of physical risks (mainly flooding risks) on their credit portfolios.

Statistics, which is a long-term survey of flood damage at a detailed spatial scale of municipalities with high accuracy. By combining the statistics with firm-level data, it has become possible to analyze the economic impact of flood damage with higher accuracy and finer granularity than in existing studies.

The three main conclusions of this paper are as follows. First, flood damage has a negative impact on the ratio of profit to sales, especially in the manufacturing industry. Second, the impact of floods on this ratio lessens in the short term. And third, the negative impact tends to be greater for firms located in municipalities that experience floods with less frequency. The magnitude of the impacts identified quantitatively in this paper can be used as part of the basic information for estimating the extent to which firms' credit costs will increase due to the occurrence of floods.

This paper is organized as follows: Section 2 surveys previous studies and describes the features of this analysis; Section 3 provides an overview of the *Flood Statistics* and financial conditions database used in this analysis; Section 4 focuses on the model used in the estimations and their results; Section 5 summarizes the results of this analysis.

2. Literature review

It is pointed out that the impact of natural disasters on the economy has started to be studied in the field of economics relatively recently, around the 2000s (e.g., Lazzaroni and Bergeijk [2014]). Economists are now taking a keen interest in assessment of the impact of natural disasters due to their frequent occurrence and the increase in intensity caused by climate change, which leads to a significant increase in empirical studies. These analyses can be broadly divided into those that focus on macroeconomic impacts and on individual entities such as firms and households.

Studies on macroeconomic impacts are mainly based on cross-country panel data, and representative studies include Skidmore and Toya [2002], Kahn [2005], Noy [2009], Strobl [2012], Hsiang and Jina [2014], and Felbermayr and Gröschl [2014]. Lazzaroni and Bergeijk [2014], who conducted a meta-analysis of 64 papers analyzing macroeconomic impacts, reported negative impacts on average for direct losses, damage to assets such as buildings and production facilities, and human losses. However, for indirect losses, which are caused by business interruptions and damage to supply chains due to natural disasters, the impact was not significant when measured by overall macroeconomic performance. On the other hand, Klomp and Valckx (2014) conducted a meta-analysis of 25 papers and concluded that natural disasters have a significant negative impact on economic growth.

Since the damage from natural disasters tends to concentrate in a confined geographical area in general, there is a limit to the analysis using coarse-grained data, and it is important to analyze the impact on individual entities. However, because it is extremely difficult to obtain data that specify the damage of individual entities by natural disaster, there are fewer studies that analyze the impact on individual entities than those that analyze the impact on the macroeconomy.

In particular, Leiter et al. [2009] and Noth and Rehbein [2019] are the only ones that deal with the impact of floods on firms' financial conditions, which is the scope of this analysis. Leiter et al. [2009] analyzed the differences in the average post-disaster performance of employment, total assets, and productivity between firms located in the affected and non-affected areas for the European floods of 2000. The results showed that firms located in the affected areas had significantly higher post-disaster growth in employment and total assets than firms located in the non-affected areas, but there was no significant difference in productivity. Noth and Rehbein [2019] analyzed the differences in post-disaster sales, tangible fixed assets, leverage ratios, and cash balances between firms located in the affected and non-affected areas for the 2013 Elbe River flood. Although there was no significant difference in the impact on tangible fixed assets, the post-disaster sales of firms located in the disaster area increased, the leverage ratio decreased, and cash increased compared to firms located in the non-disaster areas. Overall, the performance of firms located in the disaster area was better than that of firms located in the non-disaster areas.

Interestingly, in these previous studies, the impact of floods on firms' activities was not negative. One of the reasons for this is that experts have pointed out that there are limitations to the accuracy of the data used as explanatory variables to identify an exact location that experienced natural disasters, and in the data granularity used for explanatory and dependent variables.[6]

On the issue of the accuracy of disaster identification data used as explanatory variables, the limitations of the EM-DAT, which has been frequently used in previous studies, have been pointed out (Felbermayr and Gröschl [2014], Strobl [2012]). The EM-DAT provides information on natural disasters around the world, including the time and place of the events, the number of people killed or affected, and the amount of damage estimated based on insurance payments. It has advantages over other natural disaster-related databases in terms of data collection period and availability. For this reason, previous studies have frequently used data recorded in the EM-DAT as proxy variables for the specification of natural disasters. Lazzaroni and Bergeijk [2014] reported that more than 60% of the papers included in their meta-analysis used the EM-DAT. However, the EM-DAT was collected and constructed to the extent possible

[6] In addition, it is pointed out that natural disasters have a positive effect on economic activities, such as the impact of technological enhancement on the economy caused by replacing a damaged instrument with one derived from leading-edge technology. There is a possibility that such a positive effect may hamper researchers in terms of gaining negative results with statistical significance (Skidmore and Toya [2002]). This paper estimates all the impacts of floods, including positive aspects, and thus we can confirm whether the positive effects dominate when examining the results of this paper.

from a variety of sources, such as news and data on insurance payments, which raises the issue of inconsistency and coverage-insufficiency when comparing different countries and regions. For example, when comparing developed with developing countries, natural disasters occurring in developed countries tend to be included in the EM-DAT due to enriched media coverage and higher insurance penetration. In addition, developed countries tend to have higher GDP per capita, and thus there is a positive correlation between the probability of inclusion into the database and GDP per capita (Felbermayr and Gröschl [2014]). As the EM-DAT can have such a selection bias, there is a possibility that the parameter estimates will have an upward bias if we use the EM-DAT as a variable to identify natural disasters and simply estimate the impact on productivity using least squares, as many previous studies have done. This is because the latent variable of differences in data coverage between developed and less developed countries influences the parameter estimates.

In light of these problems, primary geophysical and meteorological sources tend to be used for disaster identification in recent studies, and some of which have indicated points to be considered in the usage of the EM-DAT by making a comparison between the estimation results with the EM-DAT and those with geophysical and meteorological data. For example, Strobl [2012], who analyzed the impact of hurricanes on the GDP growth rate of Central American countries, compared the estimation results of using wind speed as the data for disaster identification and those of using the values of damage and the number of deaths included in the EM-DAT. In the former case, the impact is significantly negative, while in the latter case, no significant difference is obtained.[7] Felbermayr and Gröschl [2014] analyzed the impact of natural disasters on the GDP per capita growth for up to 108 countries and found that the impact was significantly negative when primary geophysical and meteorological data were used, but significantly positive with the EM-DAT data.

Regarding the issue of granularity of the data used for explanatory and dependent variables, i.e., the fineness of the spatial scale, Botzen et al. [2019] pointed out that analysis in previous literature on the economic impact of natural disasters, which are local events, lacked spatial fitness, as it was conducted only on a regional or a national basis and emphasized the usefulness of addressing this issue in future analyses.[8]

In particular, when analyzing the impact on individual entities such as firms, it is important to use data with a finer spatial scale for both explanatory variables and explained variables, as

[7] In addition to this, Strobl [2012] finds that the EM-DAT does not contain information on several well-known damaging hurricanes in the Caribbean region in terms of comparing wind speed data, and notes that attention should be paid when analyzing the impact of hurricane strikes on the GDP growth of the region by using the data from the EM-DAT.

[8] Botzen et al. [2019] also suggests that research on long-term impacts (e.g., beyond five years) of natural disasters is still insufficient, and thus this paper attempts to analyze the 10-year impacts of floods, as well as their short-term impact.

compared to analyses of the impact on the macroeconomy, so that it helps to minimize as much as possible the estimation error of parameters brought about by observation error. Ideally, the best database for empirical analysis would be one that identifies the impact of the disaster at the level of individual entities and how the economic situation of those entities has changed over time can be observed. In practice, however, it is extremely difficult to obtain such a database that can identify the impact of disasters at the level of individual firms. Therefore, in previous studies, it was common to conduct analysis by assuming that all firms belonging to an area in a part of which a disaster occurred were evenly affected. This kind of variable treatment results in approximating with representative values the original information on whether individual firms are truly affected, which leads to observation errors. The smaller the spatial scale of disaster identification, the smaller the observation error.

Checking the spatial scales used in previous studies to identify disasters, Leiter et al. [2009] used level 2 of the EU's regional statistical classification unit (Nomenclature of territorial units for statistics; NUTS). The average population of NUTS2 ranges from 800,000 to 3 million, which is roughly equivalent to the average size of a prefecture in Japan.[9] In Noth and Rehbein [2019], flood damage was identified in terms of German counties ("Kreise"), which correspond to NUTS3. The floods are identified in units, and the average population in the areas falling under NUTS3 ranges from 150,000 to 800,000.

In order to address the issues raised in the previous studies, this paper combines *Flood Statistics* with firm-level financial data. The statistics record the damage status of almost all floods in Japan by municipality, such as the area affected and the number of buildings, at a much finer spatial scale than in most of the previous studies. By combining these data, we will conduct an analysis that enhances both the accuracy of the data for disaster identification used as explanatory variables, and the granularity of the data for explanatory and dependent variables.

3. Data

The following section details the accuracy and granularity of the data used in this paper to identify disasters and their impact on businesses.

3 - 1. *Flood Statistics*

In this paper, we improve the granularity of data for specifying floods by exploiting *Flood Statistics*, which records the detailed information on flood damage, such as the area affected and the number of buildings, for each municipality at a much finer spatial scale than most of the previous studies. That contributes to dealing with a challenge related to issues of disaster identification, as described in Section 2. *Flood Statistics* have collected information on flood

[9] About 70% of the total 47 prefectures of Japan corresponds to the NUTS2.

damage, regardless of scale, based on the results of the survey by the MLIT in prefectures and municipalities every year since 1961 under the authority of the Statistics Act for the purpose of implementing administrative measures related to flood control. The statistics cover damage to (1) private facilities such as households, business facilities, and farmland, (2) public infrastructural facilities such as river and coastal embankments and erosion control facilities, and (3) public utility facilities such as railroads, waterworks, and electrical power facilities for each municipality. Damage status is also recorded, including the area of damage –to residential and agricultural land, the number of buildings damaged by the degree of inundation, and the number of households and businesses affected. In addition, the monetary damage is calculated by multiplying by a factor such as the assessed value of assets. For example, over the 26 years from 1993 to 2018, about 5,000 business facilities were damaged annually on average, which is equivalent to 0.1% of the total business facilities.

Rather than focusing on a specific event that occurred at a certain time, as in Leiter et al. [2009] and Noth and Rehbein [2019], this paper analyses almost all floods that have occurred since 1993. Furthermore, we specify (1) whether flood damage occurred in a municipality (regardless of the target, such as households, businesses, or public engineering facilities), (2) whether flood damage occurred at businesses located in the municipality, and (3) the scale of the flood damage. To the best of the authors' knowledge, there is no empirical analysis that deals with large-scale and widespread cases of flood damage on such a fine spatial scale and with detailed information.

In order to measure the scale of flood damage, this paper uses the "ratio of flood-affected business facilities," which is the number of business facilities affected divided by the total number of business facilities[10] recorded in the Economic Census. We calculate this ratio for each municipality for each year.

3 - 2. Firm-level data

In order to analyze the impact of the flooding on the firms, we use COSMOS2, provided by Teikoku Databank, which contains financial information on millions of domestic firms, such as sales and final profits. It also includes non-financial information such as location, industry, and number of employments. The data have been recorded since 1976. It should be noted that, since the data only cover corporate bodies, the analysis in this paper does not include non-corporate agricultural workers in the sector, a category that is expected to be greatly affected by floods.[11]

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[10] The source of the total number of business facilities is taken from the Economic Census (in 2009 and beyond) and the Establishment and Enterprise Census (before 2009). Because the Census is not carried out every year, there are years without data. This paper assumes that missing data are identical to data in the previous survey.

[11] In this paper, "firm" means corporate body.

As mentioned earlier, databases that can identify the impact of disasters at the level of individual firms are extremely difficult to obtain, and this is an issue for this paper as well. However, *Flood Statistics* used to identify disasters in this analysis identify flood damage at the municipal level in Japan. The average population of a municipality is about 60,000 people; compared to previous studies, such as Leiter et al. [2009] and Noth and Rehbein [2019], we were able to create variables on a finer spatial scale.

4. Impact of floods on firms' activities

4 - 1. Empirical framework

For the estimation, we use panel data constructed by matching the location information of firms in COSMOS2 with the flood-affected business facilities by municipality in the *Flood Statistics*. By using the ratio of flood-affected business facilities, it is possible to conduct analysis that takes into account the scale of the floods. Although there is no exact correspondence between damage to business facilities and corporate bodies, a business facility is generally part or all of a firm, and the relationship between the ratio of flood-affected business facilities and that of flood-affected firms is assumed to be close. Therefore, large companies with capital of one billion yen or more were excluded from this analysis and we use the ratio of flood-affected business facilities as a proxy variable for the damage rate to firms.

In terms of our specification, Leiter et al. (2009) and Noth and Rehbein (2019) estimate the impact using DID (Difference-in-Differences), and this paper follows this approach. DID is a method of estimating the effect of a specific event by comparing the differences between the means of the samples in the treatment and in the control groups at two time points (Figure 3). Here, the treatment group is the sample group affected by a specific event, and the control group is the sample group that is not affected. It is assumed that the treatment and control groups include the common effect of time change, and that only the treatment group includes the effect of events. When applied to this paper, we divide the firms to be estimated into a treatment group and a control group based on whether the firms are located in the municipality that experienced the flooding, and then estimate the impact of the flooding by comparing the range of change in the mean values of the financial variables of the two groups before and after the flooding.

In this paper, we examine the impact of floods using multiple points in time, whereas Leiter et al. [2009] and Noth and Rehbein [2019] analyze using only a single point in time. For this reason, we follow Wooldridge [2007] and use a two-way fixed effects model, which is a general form of DID regression. Our basic specification is the following:

$$y_{i,t} = c + \alpha D^0_{i,t} + \beta D_{i,t} + \gamma H_{i,t} + \nu_i + \nu_t + \varepsilon_{i,t}. \qquad (1)$$

This specification is the same as that in Felbermayr and Gröschl [2014] and is frequently used in empirical analyses of the impact of natural disasters on economic activity, as mentioned in Botzen et al [2019]. $y_{i,t}$ is the financial data of firm i at each time t in COSMOS2. For the financial data to be analyzed, we used the value of final profit divided by sales (hereinafter referred to as the ratio of profit to sales) and the year-on-year rates of change in sales, for which long-term time series data are available.[12] $D^0_{i,t}$ is a dummy variable that takes the value of 1 if the municipality in which firm i is located at time t has experienced flood damage without damage to business facilities, and 0 otherwise. It controls for the indirect impact of floods on firms when there are no effects on business facilities in the municipality but there are on households and public facilities. $D_{i,t}$ is a dummy variable that takes the value of 1 if the ratio of flood-affected business facilities (see 3 - 1. for the calculation method) at time t of the municipality in which firm i is located is greater than zero, and 0 otherwise.[13] $H_{i,t}$ is the ratio of flood-affected business facilities at time t of the municipality in which firm i is located, which allows us to capture the impact on the firm's finances according to the scale of flood damage at the municipality level. ν_i is the fixed effect of firm i, and ν_t is the time effect to control for the trend at the same time t. The estimation period is 26 years, from 1993 to 2018, when *Flood Statistics* were available in spreadsheet format. The effects of floods do not necessarily disappear in a single year but may remain for multiple years. In this case, the effects of flooding experienced at time t and the effects of flooding experienced in the past may be included in $y_{i,t}$, and the impact may not be estimated correctly. For this reason, unless otherwise explicitly stated, cases in which floods were experienced multiple times in the past five years without the time point t are excluded from the estimation in this paper.[14] In what follows, "past h years" refers to the period from time t-1 to time t-h, and "h years since the occurrence of the flood" refers to the period from time t+1 to time t+h.

4 - 2. Descriptive statistics

The descriptive statistics of the dependent variable used in the estimation are shown in Figure 4. The average value of the year-on-year rates of change in sales is about -1.6% for the firms

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[12] In order to eliminate the distortion caused by outliers, we drop the samples below the 1st percentile and those above the 99th percentile from all samples of the year-on-year rates of change in sales and of the ratios of profit to sales.

[13] In this specification, $D_{i,t}$ shows the average difference of financial conditions between the control group and the treatment group under the condition that the ratio of flood-affected business facilities, $H_{i,t}$, is equal to 0, and it is considered that $D_{i,t}$ has almost no effects when measuring the impact of mass disasters. However, we have decided to include it in order to avoid formulation error. Our estimation results indicate that there is only a marginal contribution of $D_{i,t}$, in fact. Looking at the decomposition of a change in the ratios of profit to sales assuming about 25% of the ratio of flood-affected business facilities, as shown in 4-3, $D_{i,t}$ contributes only slightly; that is, at around 0.03% at around.

[14] Thus, the estimation results in this paper are recognized as appropriate if the impact of floods has subsided within the past five years. For more specific information, see footnote 17.

located in the areas that experienced flood damage, while it is about -1.3% for the firms located in the areas that did not, with the latter having a slightly smaller negative range. The standard deviation of the year-on-year rates of change in sales is almost the same for both, at around 22%. The average value of profit to sales is about 0.8% for both areas. The standard deviation of the ratio of profit to sales is larger for the latter, with the respective figures at 5.3% and 5.7%. The descriptive statistics of the explanatory variables are shown in Figure 5. The number of observations for data with no-flooding areas is about 17 million, and the number of observations for data with flooding areas is about 15 million, ensuring a well-balanced sample size for both.

4 - 3. Short-term impacts

This paper refers to the impact on firms' financial conditions in the year of flooding as short-term impact, which is the shortest period that can be analyzed with data on a yearly basis. Leiter et al. [2009] regard three years, including the year of flooding, as the short term. In this paper, however, when the year after the flood occurs is also included, it is treated as a long-term period.

In the estimation, a subsample estimation by industry was conducted in order to compare control and treatment groups sharing similar characteristics. In this section, to confirm the economic impact of a large flood, we estimate the parameters and present the results assuming a ratio of flood-affected business facilities of about 25%, which corresponds to the average of the annual maximum damage rate from 1993 to 2018. In order to check robustness, we also carried out estimation for alternative models and the results are provided in the Appendix.

Impact on the year-on-year rates of change in sales

In terms of the impact on the year-on-year rates of change in sales, the point estimates for all industries show a negative impact. The results of the estimates by industry also show that the point estimates of the year-on-year rates of change in sales are negative, except for the construction industry. However, none of the differences are statistically significant (Figure 6).

Impact on the ratio of profit to sales

The impact on the ratio of profit to sales has a statistically significant negative effect in the estimates for all industries. In the subsample estimation results by industry, we can confirm a significant negative impact in the manufacturing and service industries (Figure 7).[15]

Relationship between the frequency of flooding and its impact

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[15] The point estimates assuming a ratio of flood-affected business facilities of about 25% demonstrate the average for the effect on 25% of affected firms and on 75% of unaffected firms within the same municipality. Under the assumption that financial conditions of affected firms are only influenced by floods and those of unaffected firms are not, the impact on the financial condition of each firm can be interpreted as closely approximating the impact in the case assuming a 100% ratio of flood-affected business facilities. Therefore, the rough estimates of the flooding impact on an individual firm can be obtained by quadrupling the results shown in Figures 6, 7 and 8.

We confirmed the relationship between the frequency of flooding and the decline in the ratio of profit to sales, which was statistically significant for the sample of all industries. Specifically, we excluded samples that had experienced multiple floods in the past 10, 15, and 20 years prior to time t, and estimated the relationship for samples of all industries. Confirming the results in Figure 8, we can see that the lower the frequency of experiencing floods, the greater the negative impact on the ratio of profit to sales.

4 - 4. Long-term impact

For the long-term effects, we examine the impulse responses in the framework of Local Linear Projection (LLP) by Jordà [2005]. LLP has the advantage of being highly robust to errors in the formulation of the model, such as the choice of explanatory variables and the number of lags. The estimation equation takes the form

$$y_{i,t+h} = c_h + \alpha_h D^0_{i,t} + \beta_h D_{i,t} + \gamma_h H_{i,t} + \nu_i + \nu_t + \varepsilon_{i,t+h} \quad , \qquad (2)$$

where the time point of the explained variable in equation (1) is advanced by h. The coefficients γ_h obtained by estimating each case where h is from 0 to 10 for the sample of all industries, the manufacturing industry, and the construction industry are shown in Figure 9. As for all industries, a significant negative impact was identified in the year when a flood occurred, and no significant impact has been observed since then. The results in both the manufacturing industry, which sees a negative impact in the year of the flood, and the construction industry, which realizes a positive impact, show that the impact becomes insignificant within one year of the flood's occurrence, and that the impact seen as a reaction to the flood also becomes insignificant within six years of the flood's occurrence.[16]

4 - 5. Discussion

Comparing the results by financial variables, the impact on the year-on-year rates of change in sales tends to be negative in the point estimates, but in all the cases above it does not have statistically significant effects, while most of the impact on the ratio of profit to sales does have such effects. The impact on the ratio of profit to sales can be considered as capturing the magnitude of a direct loss, as Lazzaroni and Bergeijk [2014] pointed out, bearing in mind that the ratio of profit to sales can be negatively affected by impairment loss. On the other hand, the impact on the year-on-year rates of change in sales can be organized as an indirect loss since it

[16] As described in the previous paragraph, samples that experienced floods multiple times in the past five years without the time point t are excluded from the estimation. The results of long-term impact demonstrate that the impact becomes statistically insignificant within four years, excluding that of the construction industry. Because the construction industry shows a significantly negative impact five years later, to be precise, the results of both the construction industry and all industry shown in the previous paragraph may be biased slightly. In order to respond to this issue, we re-estimate the long-term impact with samples excluding those experienced multiple times in the past 10 years and confirm that the main results do not change from those in the previous paragraph.

captures the impact of production stoppages and other factors. Under this interpretation, the results of the analysis are consistent with those of the meta-analysis by Lazzaroni and Bergeijk [2014], which found a significant negative impact on direct losses but no significant difference in terms of indirect losses. These divergent estimation results may stem from the difference in the substitutability of sales and profits. As for sales, the decrease due to the inability of disaster-affected firms to operate for a certain period of time may have been compensated for by alternative supply between different points in time (but only for a few months, as described below), or by alternative supply by other firms in the same industry within the same municipality.

In the meantime, the ratio of profit to sales is likely to be affected by extraordinary losses including impairment losses from firms' asset damages and restoration costs, as mentioned above, and it is unlikely that there will be substitution as assumed in sales.

When comparing variables such as sales, where substitution occurs, and the ratio of profit to sales, where substitution does not occur, the former is unlikely to be significant in the estimation in this paper. For example, if alternative supply between different points in time by the same firms that have stopped supply activities due to the disaster takes place at a relatively early stage, such as after a few months from the disaster's occurrence, the absolute value of the parameter will be small because the financial data are on a yearly basis, and the decrease in sales over a year is hardly observed. In addition, if substitution within the same municipality arises to a large extent, this means that there exist two types of firms: those for which sales decrease due to flooding and those for which sales increase due to substitution. If there is complete substitution within a municipality, the estimated results are still unlikely to be significantly different because the impact of the flood will be zero for the entire municipality and the dispersion among firms will be large.[17] In order to confirm this point, we estimated whether the standard deviations of the year-on-year rates of change in sales and the ratio of profit to sales within a municipality would increase in the municipality that experienced the flood.[18] The results showed that the standard deviation of the year-on-year rates of change in sales increased significantly at the 10% significance level in the municipalities that experienced the flooding, while no significant difference was found for the ratio of profit to sales at the 10% significance level. From both

[17] The ratio of flood-affected business facilities, $H_{i,t}$, used in this paper represents the damage rate of the municipality overall, and thus it is worth keeping in the mind that, even in the case where $H_{i,t}$ is greater than zero, both flood-affected firms and non-affected firms exist within the same municipality.

[18] As the explained variables, we used the standard deviations of figures, which are obtained by subtracting the time and the fixed effects by industry shown in equation (1) from the year-on-year rate of changes in sales and the ratio of profit-to-sales of each firm i, respectively. As the explanatory variables, we used the dummy variable of $D_{i,t}$, which can identify whether the municipality experienced floods at time t. For the estimation, the two-way fixed effects model was used in order to take into account both the fixed effect for each municipality and industry and the time effect. The estimation is carried out with all firms for which we were able to compute the explained variables. The number of observations is 142,308.

results, the data confirmed the possibility of substitution occurring within the same municipality when floods occur. In addition to this, a comparison of the results for each industry in Figures 6 and 7 shows that the magnitude of the impact of the year-on-year rates of change in sales is consistent with the magnitude of the impact of the ratio of profit to sales. This suggests that sales is one of the appropriate indicators for measuring the impact of flood damage on individual firms, and that more granular data on the damage to individual companies would be useful in identifying a negative effect. Since the standard deviation of the year-on-year rates of change in sales in the areas affected by the floods and the impact of the floods by industry tended to be the same in terms of both ratios, it is considered that there is a reasonable possibility that year-on-year rates of change in sales have been negatively affected by the floods on an individual firm basis.

As for the results of the ratio of profit to sales by industry, the reason behind the large negative impact on the manufacturing industry is that it is an equipment industry, and as such, production facilities are prone to entail impairment and recovery costs. This interpretation is consistent with the above description, which suggests that the downward pressure on the ratio of profit to sales is mainly due to extraordinary losses. Another possible reason is that the manufacturing industry is considered to be more susceptible to alternative supply by other companies in the same industry within the same municipality than by the service industry or the wholesale retail industry. The positive impact of the construction industry, although not significant, is likely due to reconstruction demand.

Furthermore, examining the relationship between the frequency of flooding and the extent of the decline in firms' ratio of profit to sales shows a trend where the lower the frequency of flooding, the greater the negative impact on firms' ratio of profit to sales. This result can be interpreted as suggesting that firms located in areas that experience floods more frequently may be able to mitigate the damage through preparedness.

Moreover, as can be seen in Figure 9, the negative impact of floods on the ratio of profit to sales converges in a relatively short period of time. Since extraordinary losses are exceptional and not recorded on a recurring basis, this is consistent with the earlier point made that the downward pressure on the ratio of profit to sales is mainly due to extraordinary losses.

Lastly, as we described in –Section 2, we exploited a much finer spatial scale than in most of the previous studies to reduce observation error. In order to confirm the effect, we aggregated the ratio of flood-affected business facilities by prefecture, and the estimation results are shown in Figures A-6 and A-7.[19] In the result for ratio of profit to sales, no significant differences were found for all industries. In addition, there is no significant difference in any of the estimation results for the year-on-year rates of change in sales. There is no longer a

[19] The population of Japan's prefectures is roughly equivalent to NUTS2.

characteristic difference by industry, which is confirmed in the results by municipality. This result suggests that, when disasters are identified on a coarse spatial scale, the parameters are not estimated accurately due to observation errors in the explanatory variables.

5. Conclusion

In this paper, we analyzed the impact of flood damage on firms' financial conditions by combining *Flood Statistics* with financial data of individual firms, and statistically confirmed the point that flood damage has a negative impact on firms' financial conditions, which had not been confirmed in previous studies. The following are three specific results. First, flood damage has a negative impact on the ratio of profit to sales, especially in the manufacturing industry. Second, the impact of floods on this ratio lessens in the short term. Third, the negative impact on the ratio of profit to sales tends to be greater for firms located in municipalities that experience floods less frequently. We also found that the magnitude of the negative impact differs depending on the firms' characteristics, such as industry.

The first result suggests that financial institutions need to work on managing physical risks. Furthermore, the result that the impact varies by firms' characteristics means that the impact of physical risks faced by lending firms can vary by firm attribute, which is an important result for financial institutions that try to enhance their framework of risk management in response to risk characteristics. In Japan, where the frequency of floods is expected to increase as climate change progresses, financial institutions need to be aware that the characteristics for physical risks vary depending on lending firms, and they should pay close attention to the possibility that floods may cause more deterioration in firms' financial conditions than ever before.

One challenge for the future is to examine the impact of floods on banks' balance sheets as well as the transmission mechanism. The results of this paper suggest that impairment losses can be a source of deterioration in firms' financial conditions; in other words, from banks' point of view, an impact on collateral values may exist and that could harm banks' balance sheets. As this issue is not within the scope of this paper and the accumulation of empirical analyses seems not to be sufficient, further investigation is needed.

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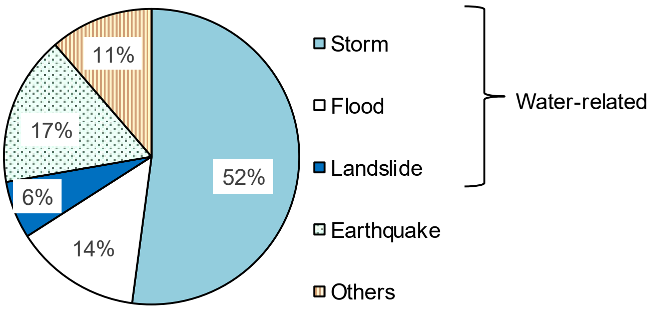
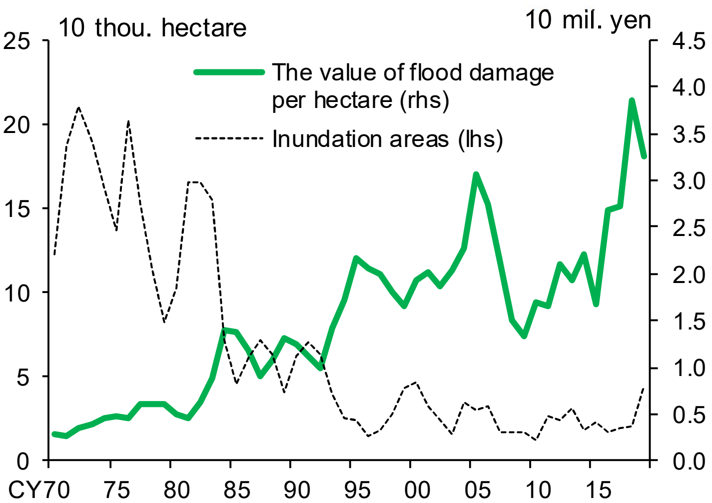
Figure 1. The number of catastrophes that occurred in Japan by disaster type



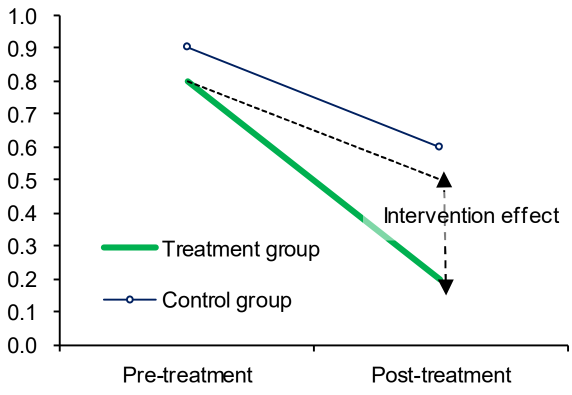
Note: 1. The EM-DAT contains global catastrophes that conform to at least one of following criteria: (1) 10 or more people dead, (2) 100 or more people affected, (3) the declaration of a state of emergency, and (4) a call for international assistance.
Note 2: The figure includes 238 catastrophes that occurred in Japan from 1980 to 2020.
Source: EM-DAT, CRED / UCLouvain, Brussels, Belgium – www.emdat.be (D.Guha-Sapir).

Figure 2: Developments in flood damage in Japan



Note: 3-year backward moving averages. The figures for the value of flood damage are at 2011 prices and the latest data represent a 2019 provisional value with a 2018 deflator. The value of flood damage includes damage to assets of households and businesses, public engineering facilities, public utility facilities such as railroads and communication facilities, and caused by water-related disasters such as floods and surges.
Source: Ministry of Land, Infrastructure, Transport and Tourism.

Figure 3: Difference-in-Differences estimation



Note: The control group is the set that is not affected by the event under analysis. The treatment group is the set that is affected by the event under analysis.

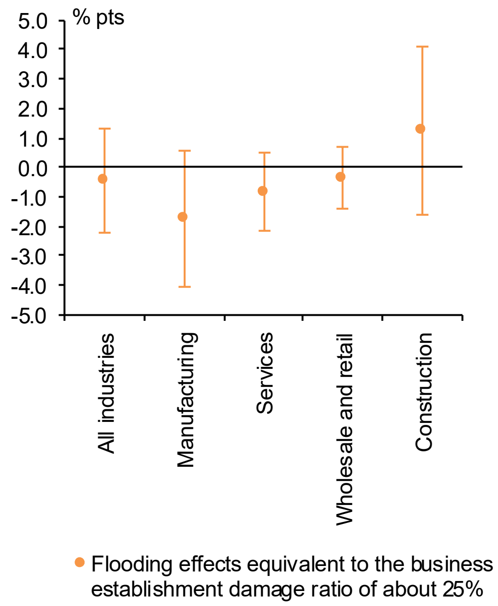
Figure 4: Descriptive statistics for the dependent variables

	Treatment	Mean	SD	Min	Max	Observations
Year-on-year rates of change in sales	0	-0.0158	0.222	-1.002	1.001	15,704,363
	1	-0.0131	0.220	-1.002	1.001	14,446,914
Profit to sales	0	0.00730	0.0533	-0.326	0.229	10,282,655
	1	0.00766	0.0564	-0.326	0.229	8,568,243

Figure 5: Descriptive statistics for the explanatory variables

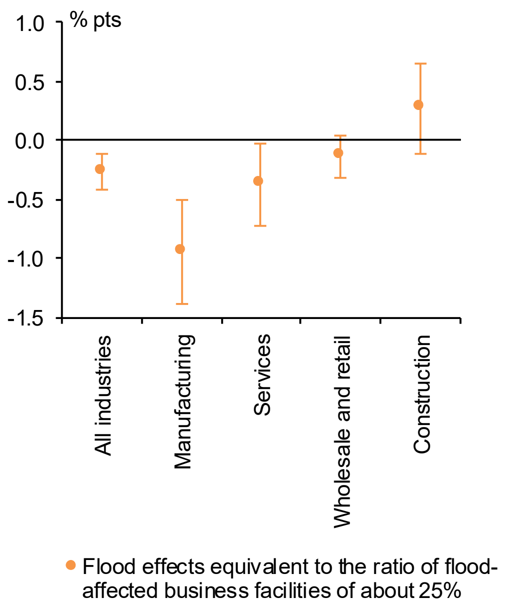
	Treatment	Mean	SD	Min	Max	Observations
$D^0_{i,t}$	0	0	0	0	0	16,971,772
	1	0.61	0.49	0	1	15,542,627
$D_{i,t}$	0	0	0	0	0	16,971,772
	1	0.39	0.49	0	1	15,542,627
$H_{i,t}$	0	0	0	0	0	16,971,772
	1	0.00121	0.00837	0	0.50	15,542,627

Figure 6: Year-on-year rates of change in sales



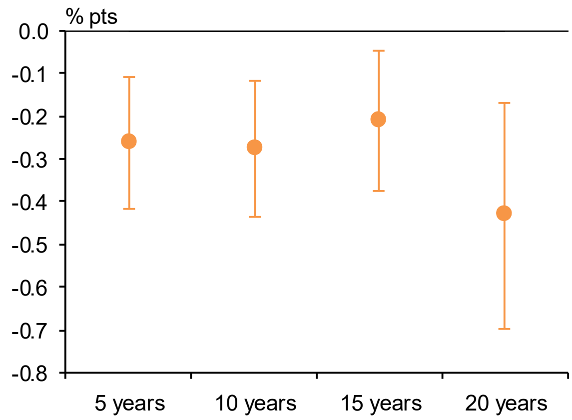
Note: 1. The error bar indicates a 95 percent confidence interval.
2. "Wholesale and retail" includes food services.
3. The estimation uses the unbalanced panel data from 1993 to 2018.

Figure 7: Ratio of profit to sales



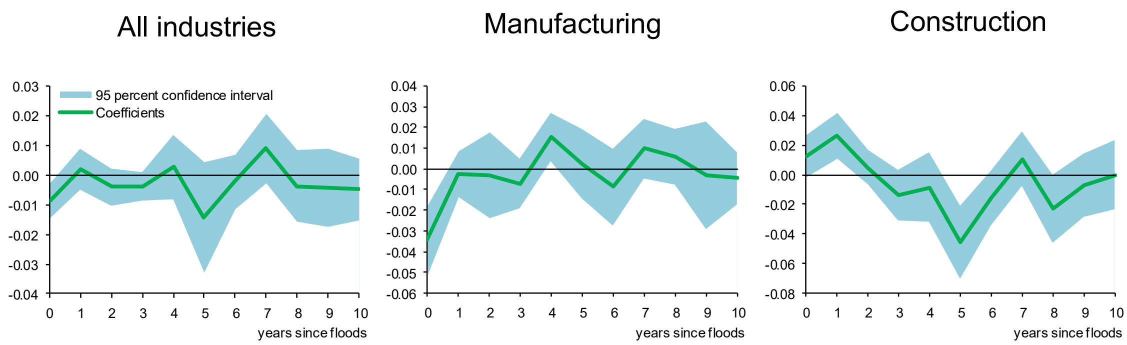
Note: 1. The error bar indicates a 95 percent confidence interval.
2. "Wholesale and retail" includes food services.
3. The estimation uses the unbalanced panel data from 1993 to 2018.

Figure 8: Frequency of flooding and ratio of profit to sales



Note: 1. The error bar indicates a 95 percent confidence interval.
2. The figures indicate the estimation results for firms that have not experienced floods more than once in each observation period. "5 years," "10 years," "15 years," and "20 years" indicate the periods of observation for the estimation.

Figure 9: Coefficients for ratio of flood-affected business facilities



Note: Estimations are for firms included in "5 years" in Figure 8 for which financial variables are available in each period.

Appendix: Estimation results for alternative models

Figure A-1: Estimation results for model 1

Model 1: $y_{i,t} = c + \beta D_{i,t} + \nu_i + \nu_t + \varepsilon_{i,t}$

		$D_{i,t}$		$Constant$	
Profit to sales	All industries	-0.000057	( ) ( )	0.005582	(***) (***)
	Manufacturing	-0.000226	(***) (**)	0.008166	(***) (***)
	Services	-0.000116	( ) ( )	0.014421	(***) (***)
	Wholesale and retail	-0.000148	(***) (**)	0.004597	(***) (***)
	Construction	-0.000074	( ) ( )	-0.001319	(***) (***)
Year-on-year rates of change in sales	All industries	0.000721	(***) (**)	-0.013659	(***) (***)
	Manufacturing	-0.001238	(***) (**)	-0.016453	(***) (***)
	Services	0.001389	(***) (***)	-0.001184	(***) (***)
	Wholesale and retail	0.000444	(**) ( )	-0.019659	(***) (***)
	Construction	0.000610	(*) ( )	-0.016628	(***) (***)
Year-on-year rates of change in number of employees	All industries	0.000144	( ) ( )	-0.009019	(***) (***)
	Manufacturing	-0.000711	(***) (**)	-0.013211	(***) (***)
	Services	0.000931	(***) (***)	-0.003052	(***) (***)
	Wholesale and retail	0.000374	(**) (*)	-0.011003	(***) (***)
	Construction	-0.000110	( ) ( )	-0.009126	(***) (***)

Note: (*), (**), and (***) denote significance at the 10%, 5%, and 1% levels, respectively. For the calculation, clustered standard errors at the levels of firms (indicating in the upper cell) and municipalities (lower cell) in each year are used.

Figure A-2: Estimation results for model 2

Model 2: $y_{i,t} = c + \beta H_{i,t} + \nu_i + \nu_t + \varepsilon_{i,t}$

		$H_{i,t}$		$Constant$	
Profit to sales	All industries	-0.000006	( ) ( )	0.005571	(***) (***)
	Manufacturing	-0.000213	(***) (***)	0.008137	(***) (***)
	Services	-0.000038	( ) ( )	0.014399	(***) (***)
	Wholesale and retail	-0.000039	( ) ( )	0.004570	(***) (***)
	Construction	0.000160	(***) (**)	-0.001340	(***) (***)
Year-on-year rates of change in sales	All industries	0.000060	( ) ( )	-0.013526	(***) (***)
	Manufacturing	-0.000426	(***) (*)	-0.016658	(***) (***)
	Services	0.000023	( ) ( )	-0.000902	(***) (***)
	Wholesale and retail	0.000122	( ) ( )	-0.019579	(***) (***)
	Construction	0.000239	( ) ( )	-0.016536	(***) (***)
Year-on-year rates of change in number of employees	All industries	0.000056	( ) ( )	-0.008995	(***) (***)
	Manufacturing	-0.000170	( ) ( )	-0.013334	(***) (***)
	Services	0.000039	( ) ( )	-0.002864	(***) (***)
	Wholesale and retail	0.000088	( ) ( )	-0.010934	(***) (***)
	Construction	0.000182	( ) ( )	-0.009154	(***) (***)

Note: (*), (**), and (***) denote significance at the 10%, 5%, and 1% levels, respectively. For the calculation, clustered standard errors at the levels of firms (indicating in the upper cell) and municipalities (lower cell) in each year are used.

Figure A-3: Estimation results for model 3

Model 3: $y_{i,t} = c + \beta H_{i,t} + \theta H_{i,t} F_{it}^{5} + \nu_i + \nu_t + \varepsilon_{i,t}$

		$H_{i,t}$	$H_{i,t}F_{it}^{5}$	$Constant$
Profit to sales	All industries	-0.000103 (***) (*)	0.000035 (**) (*)	0.005939 (***) (***)
	Manufacturing	-0.000424 (***) (***)	0.000088 (***) (***)	0.008374 (***) (***)
	Services	-0.000182 ( ) ( )	0.000042 ( ) ( )	0.013872 (***) (***)
	Wholesale and retail	-0.000036 ( ) ( )	0.000001 ( ) ( )	0.004605 (***) (***)
	Construction	0.000133 (*) ( )	0.000008 ( ) ( )	-0.000150 (***) (***)
Year-on-year rates of change in sales	All industries	-0.000184 ( ) ( )	0.000064 ( ) ( )	-0.019126 (***) (***)
	Manufacturing	-0.000943 (***) (*)	0.000206 (**) ( )	-0.019720 (***) (***)
	Services	-0.000202 ( ) ( )	0.000056 ( ) ( )	-0.010283 (***) (***)
	Wholesale and retail	-0.000124 ( ) ( )	0.000097 (*) ( )	-0.025259 (***) (***)
	Construction	0.000336 ( ) ( )	-0.000071 ( ) ( )	-0.019690 (***) (***)
Year-on-year rates of change in number of employees	All industries	-0.000164 ( ) ( )	0.000055 (*) ( )	-0.011864 (***) (***)
	Manufacturing	-0.000661 (***) (*)	0.000173 (**) (**)	-0.015222 (***) (***)
	Services	-0.000145 ( ) ( )	0.000054 ( ) ( )	-0.007202 (***) (***)
	Wholesale and retail	-0.000139 ( ) ( )	0.000070 ( ) ( )	-0.013676 (***) (***)
	Construction	0.000170 ( ) ( )	-0.000023 ( ) ( )	-0.011206 (***) (***)

Note: 1. (*), (**), and (***) denote significance at the 10%, 5%, and 1% levels, respectively. For the calculation, clustered standard errors at the levels of firms (indicating in the upper cell) and municipalities (lower cell) in each year are used.

2. F_{it}^{5} is a variable representing the number of times that municipality i has experienced flooding in the past 5 years counting from time $t-1$, and it represents the frequency of flooding experienced by each city, town, and village.

Figure A-4: Estimation results for model 4

Model 4: $y_{i,t} = c + \beta H_{i,t} + \theta H_{i,t} F_{it}^{10} + \nu_i + \nu_t + \varepsilon_{i,t}$

		$H_{i,t}$		$H_{i,t}F_{it}^{10}$		$Constant$	
Profit to sales	All industries	-0.000099	(***) (*)	0.000019	(**) (*)	0.006270	(***) (***)
	Manufacturing	-0.000391	(***) (***)	0.000048	(**) (**)	0.008592	(***) (***)
	Services	-0.000199	( ) ( )	0.000050	(*) ( )	0.013719	(***) (***)
	Wholesale and retail	-0.000026	( ) ( )	-0.000006	( ) ( )	0.004563	(***) (***)
	Construction	0.000156	(**) ( )	-0.000006	( ) ( )	0.000974	(***) (***)
Year-on-year rates of change in sales	All industries	-0.000127	( ) ( )	0.000031	( ) ( )	-0.022190	(***) (***)
	Manufacturing	-0.000980	(***) (**)	0.000115	(**) ( )	-0.021161	(***) (***)
	Services	0.000001	( ) ( )	-0.000005	( ) ( )	-0.015652	(***) (***)
	Wholesale and retail	-0.000041	( ) ( )	0.000037	( ) ( )	-0.027952	(***) (***)
	Construction	0.000557	( ) ( )	-0.000061	( ) ( )	-0.021589	(***) (***)
Year-on-year rates of change in number of employees	All industries	-0.000174	( ) ( )	0.000031	(*) ( )	-0.014285	(***) (***)
	Manufacturing	-0.000416	(*) ( )	0.000043	( ) ( )	-0.016770	(***) (***)
	Services	0.000047	( ) ( )	0.000025	( ) ( )	-0.010751	(***) (***)
	Wholesale and retail	-0.000162	( ) ( )	0.000035	( ) ( )	-0.015923	(***) (***)
	Construction	-0.000043	( ) ( )	0.000013	( ) ( )	-0.013097	(***) (***)

Note: 1. (*), (**), and (***) denote significance at the 10%, 5%, and 1% levels, respectively. For the calculation, clustered standard errors at the levels of firms (indicating in the upper cell) and municipalities (lower cell) in each year are used.

2. F_{it}^{10} is a variable representing the number of times that municipality i has experienced flooding in the past 10 years counting from time $t-1$, and it represents the frequency of flooding experienced by each municipality.

Figure A-5: Estimation results for model 5

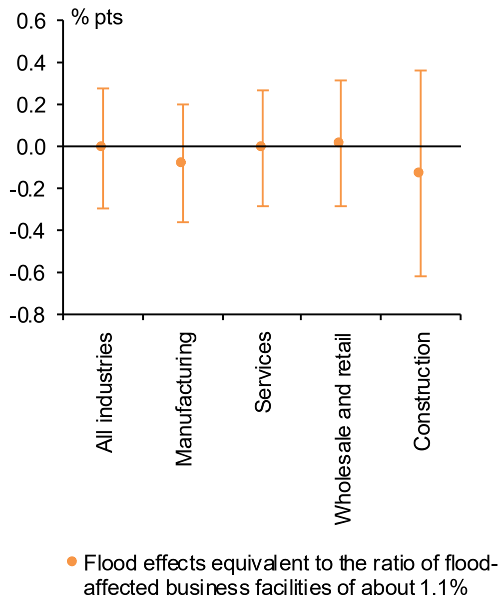
Model 5: $y_{i,t} = c + \beta H_{i,t} + \sum_{j=1}^{6} \delta^j d_{it}^j H_{i,t} + \nu_i + \nu_t + \varepsilon_{i,t}$

		$H_{i,t}$	$H_{i,t}F_{it}^{10}$	δ^1	δ^2	δ^3	δ^4	δ^5	δ^6	$Constant$
Profit to sales	All industries	-0.000054 ( ) ( )	-0.000012 ( ) ( )	-0.000162 ( ) ( )	0.000144 ( ) ( )	0.000164 ( ) ( )	0.000213 (*) ( )	-0.000064 ( ) ( )	-0.000064 ( ) ( )	0.005940 (***) (***)
	Manufacturing	-0.000684 (***) (**)	0.000312 ( ) ( )	0.000697 (**) (**)	0.001166 (**) (*)	0.000820 (***) (*)	0.000814 (***) (***)	0.000263 ( ) ( )	0.000263 ( ) ( )	0.008374 (***) (***)
	Services	0.000024 ( ) ( )	-0.000175 ( ) ( )	-0.000074 ( ) ( )	-0.001085 ( ) ( )	-0.000063 ( ) ( )	0.000216 ( ) ( )	-0.000191 ( ) ( )	-0.000191 ( ) ( )	0.013874 (***) (***)
	Wholesale and retail	-0.000123 ( ) ( )	0.000078 ( ) ( )	0.000149 ( ) ( )	0.000413 (*) ( )	0.000238 ( ) ( )	0.000060 ( ) ( )	0.000001 ( ) ( )	0.000001 ( ) ( )	0.004604 (***) (***)
	Construction	0.000233 ( ) ( )	-0.000053 ( ) ( )	-0.000878 (**) (**)	0.000259 ( ) ( )	0.000160 ( ) ( )	-0.000022 ( ) ( )	-0.000238 ( ) ( )	-0.000238 ( ) ( )	-0.000148 (***) (***)
Year-on-year rates of change in sales	All industries	-0.000073 ( ) ( )	0.000129 ( ) ( )	-0.001520 (**) ( )	-0.000891 ( ) ( )	-0.000440 ( ) ( )	0.000392 ( ) ( )	0.000314 ( ) ( )	0.000314 ( ) ( )	-0.019115 (***) (***)
	Manufacturing	-0.001185 ( ) ( )	0.000400 ( ) ( )	0.001285 ( ) ( )	-0.000234 ( ) ( )	0.001266 ( ) ( )	0.001408 ( ) ( )	0.001008 ( ) ( )	0.001008 ( ) ( )	-0.019718 (***) (***)
	Services	0.001307 ( ) ( )	-0.001187 ( ) ( )	-0.004398 (***) (*)	-0.003785 (*) ( )	-0.000771 ( ) ( )	-0.001328 ( ) ( )	-0.000827 ( ) ( )	-0.000827 ( ) ( )	-0.010276 (***) (***)
	Wholesale and retail	-0.000215 ( ) ( )	0.000322 ( ) ( )	-0.000417 ( ) ( )	-0.001130 ( ) ( )	-0.000624 ( ) ( )	0.000700 ( ) ( )	0.001033 ( ) ( )	0.001033 ( ) ( )	-0.025249 (***) (***)
	Construction	0.001936 ( ) ( )	-0.001389 ( ) ( )	-0.006553 (***) (**)	-0.001469 ( ) ( )	-0.001993 ( ) ( )	-0.001623 ( ) ( )	-0.002374 ( ) ( )	-0.002374 ( ) ( )	-0.019680 (***) (***)
Year-on-year rates of change in number of employees	All industries	-0.000387 ( ) ( )	0.000356 ( ) ( )	-0.000062 ( ) ( )	-0.000593 ( ) ( )	0.000291 ( ) ( )	0.000514 ( ) ( )	0.000659 ( ) ( )	0.000659 ( ) ( )	-0.011858 (***) (***)
	Manufacturing	-0.000888 ( ) ( )	0.000453 ( ) ( )	0.000242 ( ) ( )	-0.001889 ( ) ( )	0.001677 (*) (*)	0.001048 ( ) ( )	0.001217 ( ) ( )	0.001217 ( ) ( )	-0.015214 (***) (***)
	Services	0.000167 ( ) ( )	-0.000160 ( ) ( )	-0.000821 ( ) ( )	-0.002007 ( ) ( )	0.000104 ( ) ( )	-0.000184 ( ) ( )	0.000294 ( ) ( )	0.000294 ( ) ( )	-0.007199 (***) (***)
	Wholesale and retail	0.000345 ( ) ( )	-0.000403 ( ) ( )	-0.000738 ( ) ( )	0.000346 ( ) ( )	-0.000674 ( ) ( )	-0.000004 ( ) ( )	-0.000091 ( ) ( )	-0.000091 ( ) ( )	-0.013678 (***) (***)
	Construction	-0.000621 ( ) ( )	0.000939 ( ) ( )	-0.000129 ( ) ( )	0.000311 ( ) ( )	0.000021 ( ) ( )	0.000725 ( ) ( )	0.000778 ( ) ( )	0.000778 ( ) ( )	-0.011195 (***) (***)

Note: 1. (*), (**), and (***) denote significance at the 10%, 5%, and 1% levels, respectively. For the calculation, clustered standard errors at the levels of firms (indicating in the upper cell) and municipalities (lower cell) in each year are used.

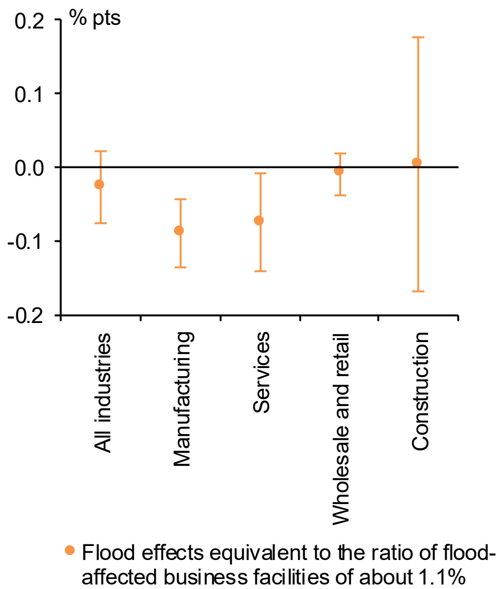
2. d_{it}^j is a is a dummy variable that takes the value of 1 if the municipality i has experienced flooding j times in the past 5 years counting from time $t-1$, and it represents the frequency of flooding experienced by each municipality.

Figure A-6: Year-on-year rates of change in sales by prefecture-level data



Note: 1. The error bar indicates a 95 percent confidence interval.
2. "Wholesale and retail" includes food services.
3. The estimation uses the unbalanced panel data from 1993 to 2018.

Figure A-7: Ratio of profit to sales by prefecture-level data



Note: 1. The error bar indicates a 95 percent confidence interval.
2. "Wholesale and retail" includes food services.
3. The estimation uses the unbalanced panel data from 1993 to 2018.