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Natural Disasters and Firm Selection: Heterogeneous Effects of Flooding Events on Manufacturing Sectors in Japan

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Abstract

Recently, natural disasters and extreme weather events have been occurring more frequently. This study examines how large floods affect the value of manufacturing product shipments and the number of facilities in the long run using municipality-level data in Japan. We considered the impacts of flooding depending on the size of the facilities and past flood experiences (leading to flood preparedness in advance). We found "build back better" dynamics, in which the value of manufacturing product shipments grew in cities affected by floods. We also found that large facilities increased, while small and mid-sized facilities decreased following floods. These results suggest two important mechanisms characterizing the damage and recovery processes of floods. First, large facilities were more resilient to flooding, while small and mid-sized facilities were more vulnerable to flooding. Economies of scale resulting from small facilities exit, and an increase in large facilities may increase the number of shipments of manufactured goods per facility. Experience with past floods did not affect the activities of large facilities. In frequently flooded cities, the activity levels of small and mid-sized facilities recovered to predisaster trends. In rarely flooded cities, a long-term decline was observed in the business activities of small and mid-sized facilities because they likely needed to revise their supply chains due to unexpected events. In addition, unexpected flooding had devastating effects on employment.

JEL classification: Q54, O18, R11

Keywords: Flood, climate change, manufacturing sectors, firm selection, past experience of floods

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1. Introduction

Recently, natural disasters and extreme weather events have been occurring more frequently. Many studies that examined the impact of disasters on the economy have tended to focus on the extent of the damage using country-level data (e.g., Dell et al., 2012; Hsiang and Jina, 2014; Kocornik-Mina and McDermott, 2020). However, the results of these studies differ from study to study: some disasters reportedly have a positive impact on economic growth while others have a negative impact, some disasters cause long-lasting damage while others cause short-term damage, and so on. The mechanism of how disasters affect the economy is not well understood. To understand this mechanism, some studies have focused on the spatial heterogeneity of damage and sector heterogeneity using plant-level data, but the number of such studies is limited (e.g., Cole et al., 2019; Okubo and Strobl, 2021). This study aims to understand the mechanism of how floods caused by extreme weather events affect production in manufacturing sectors using municipality-level data in Japan.

Previous studies mainly used country-level data to estimate the impacts of disasters on the economy and compared the results between developing and developed countries. Skidmore and Toya (2002) focused on historical natural disasters, including earthquakes, tsunamis, volcanic eruptions, and floods. They found that climatic events were positively related to long-term economic growth. Cunado and Ferreira (2014) found that flood shocks had a direct positive impact on the agricultural sector and an indirect positive impact on the nonagricultural sector, yet these effects were limited to developing countries and moderate floods. However, Hsiang and Jina (2014) obtained different results by using the exposure of each country to all tropical cyclones from 1950–2008. They found that national incomes were reduced by cyclones incidences and that the incomes do not recover within twenty years. Dell et al. (2012) found that higher temperatures substantially reduced economic growth in poor countries and that the effects persisted in the medium run.

Other have studies focused on postdisaster economic activities using nighttime light data (Elliott et al. 2015; Kocornik-Mina and McDermott, 2020). Kocornik-Mina and McDermott (2020) found that low-elevation areas recovered as rapidly as areas located at higher elevations when cities flooded, and no permanent movement of economic activities in response to floods was found. This result suggested that there was no significant adaptation, at least in the sense of the relocation of economic activities away from the most vulnerable locations. Testa (2021) focused on the role of institutions in postearthquake population recovery and found sustained negative effects of earthquakes on city population growth, with effects driven by cities located outside of stable democracies.

These macrolevel studies were insufficient to provide useful information for constructing local disaster prevention policies because they lacked insights into microlevel heterogeneity, such as municipalities, households, and firms. Some studies used plant-level data to consider the spatial heterogeneity in damage. Tanaka (2015) showed that the 1995 Kobe earthquake's negative impact on plant growth persisted for three years. Elliott et al. (2019) found that the impact of typhoons on the plant sales of Chinese manufacturers was substantial, but this effect was relatively short-lived.

One of the important mechanisms by which natural disasters can impact firms is through the "natural selection" of firms. Uchida et al. (2014) found that the rate of closure of firms due to bankruptcy decreased after the Tohoku earthquake in Japan, perhaps due to aid, and that firm exits following the earthquake were predominantly voluntary closures, with firms seizing the moment to leave an aging market. Cole et al. (2019) focused on the 1995 Kobe earthquake in Japan as a natural experiment. They used ex post damage measurements of the earthquake to show that damaged plants were more likely to fail than undamaged plants and that this effect persisted for up to 7 years. They also found a 'build back better' effect in which continuing plants experienced a temporary increase in productivity following the earthquake. Craioveanu and Terrell (2016) considered the impact of Hurricane Katrina on firm survival using a spatial Bayesian analysis and showed that firms with less flooding and firms with larger chain stores were more likely to survive. They also found that locally owned businesses opened faster than large chain stores. Okubo and Strobl (2021) considered heterogeneity among manufacturing, wholesale, retail, and construction industries. They found that the storm surge caused by Ise Bay Typhoon increased the probability of firm closures in some industries, but in other industries, it either had no effect or reduced firm exit. They also found that the impact of the storm surge on firm performance after the event varied from firm to firm.

In terms of understanding the mechanisms by which natural disasters affect the economy, the contributions of this study are as follows. The first contribution is the experience of past floods. Cities that experienced significant flooding in the past are likely to differ from those that did not experience significant flooding in relevant ways. For example, they may be better prepared for floods, with better infrastructure and more funds allocated for postflood reconstruction, which may mitigate the impact. Neumayer et al. (2014) found that past flood experience drives current cities to take proactive measures. If so, firms may relocate their facilities to cities with better flood protection. In other words, the number of facilities may tend to increase in cities with more experience with past floods, while it may tend to decrease in cities with less experience with past floods.

Second, the effect of floods on facilities may differ depending on the size of the facility. For example, smaller facilities have less money to spend on flood protection in advance. If so, such facilities would be unable to continue their business due to heavy damage. As a result, the number of small facilities would be likely to decrease after a major flood. The number of larger facilities may not decrease even after the flood if large facilities can afford to take precautionary measures. To focus on the size of facilities, facilities were classified into three categories based on the number of employees: small facilities with fewer than 10 employees, mid-sized facilities with 10–299 employees, and large facilities with more than 300 employees.

To identify the immediate and long-run impacts of large floods on manufacturing sectors, we adopt a finite distributed lag model of order ten periods. The flood data are obtained from the Dartmouth Flood Observatory (DFO), which provides detailed information on flood events such as location, timing, duration, severity indicator, causes, and other information for thousands of flood events worldwide from 1985 to 2015 (Brakenridge, n.d.). Not all floods are recorded in this database; it contains only those that have caused severe damage, for example, deaths or severe damage to structures and agriculture. Therefore, it is possible to exclude fixed effects associated with different vulnerabilities to flooding in different locations and consider what the consequences would be if the same level of damage occurred. Using this database, this study obtained the number of severe floods each city has experienced in the past. Since the interest of this study is in the effects of past flood experience on the speed of recovery and the postdisaster change in the number of facilities, a dummy variable was created to distinguish between cities with more and fewer frequent floods in the past.

The primary findings are as follows. 1) Last year floods have a negative and statistically significant effect on the value of shipment of manufactured goods and the number of facilities. 2) A "build back better" effect, in which the shipment of manufactured goods grows in cities affected by floods, is found. 3) Large facilities increase following floods, while small and mid-sized facilities decrease. These results suggest two important insights for the adaptive behavior of manufacturing sectors. First, larger facilities are more resilient to flooding, while smaller facilities are vulnerable to flooding. Second, economies of scale resulting from an increase in the number of larger facilities may cause the "build back better" dynamic, which increases the value of manufactured products shipped per facility. In terms of the experience of severe flooding in the past, it was found that 4) in frequently flooded cities, the activity levels of small and mid-sized facilities recover to predisaster levels; in rarely flooded cities, a long-term decline occurs in the business activities of small and mid-sized facilities. However, it was also found that 5) the experience of past floods does not affect the activities of large facilities. Finally, it was found that 6) unexpected flooding has devastating effects on employment, which is a serious issue for the regional economy.

The remainder of this publication is organized as follows. Section 2 introduces the data and provides descriptive statistics. Section 3 describes the estimation strategy. Section 4 presents the main results. Section 5 concludes.

2. Data

A balanced panel was compiled at the city level in Japan with annual data on the number and physical intensity of floods and economic variables of manufacturing sectors. We selected 1729 cities during the 2002–2010 period. There are two reasons why the sample period was extended from 2002 to 2010. The first reason is that floods with a severity of 1.5 or higher occurred somewhere in Japan every year during this period except for 2003, and the second reason is to remove the effect of the Great East Japan Earthquake in 2011. Since a finite distributed-lag model was used with 10-year lags on the explanatory variable (i.e., a flood variable), the number and physical intensity of floods was added in the period 1992–2001 to the panel data. The data were drawn from some sources as detailed below.

Floods

The flood variables used in this study come from the Dartmouth Flood Observatory (DFO) archive (Brakenridge, n.d.). The DFO database includes location, timing, duration, severity indicator, and other information for thousands of flood events worldwide from 1985 to 2015. These data were compiled from a wide variety of media estimates, governmental sources, and satellite images based on the MODIS (Moderate Resolution Imaging Spectroradiometer, http://modis.gsfc.nasa.gov) and optical remote sensing and passive microwave remote sensing[1], which provide frequent updates of water conditions worldwide to detect and locate flood events. For a flood event to be considered "large" and recorded in the dataset, it must meet at least one of the following criteria: "Significant damage to structures or agriculture, long reporting interval (decades) since the last similar event, and/or fatalities". Floods are divided into three severity classes depending on their estimated recurrence interval. Class 1 floods have a 10- to 20-year-long reported interval between similar events, class 1.5 floods have a 20- to 100-year recurrence interval, and class 2 floods have a recurrence interval greater than 100 years.

Economic data of manufacturing sectors

1 AMSR-E and TRMM sensors monitoring approximately 10,000 areas (http://old.gdacs.org/flooddetection/)

Data on the value of shipments of manufactured goods, the number of facilities, and the number of employees at the end of the year was used for each of the approximately 1,800 cities from the Census of Manufacture Achieves by Ministry of Economy, Trade, and Industry (METI), Japan. The census was conducted to clarify the actual conditions of Japan's manufacturing industry and to obtain basic data for industrial policies. The data were available annually from 1979 to 2015. Facilities were divided into four groups in terms of the size of facilities: facilities of any size; small facilities with fewer than 10 employees; mid-sized facilities with 10–299 employees; and large facilities with more than 300 employees. In this dataset, if the number of facilities was equal to one (i.e., there was only one firm in the municipality), the numerical value of shipments and employees was not listed.

3. Empirical strategies

To identify the immediate (i.e., following year) and longer-run impact of large floods on manufacturing sectors, data from city i in year t (t = 2002–2010) were used, and a distributed-lag approach that controls for a finite number of lags on the explanatory variable was adopted (Dell et al. 2012; Testa, 2021):

$$\ln(Y_{it}) = \sum_{s=1}^{10} \beta_s Flood_{i,t-s} + City_i + Year_t + e_{it}\,, \tag{1}$$

where Y_{it} is our set of dependent variables including the value of shipment of manufactured goods, the number of facilities, and the number of employees for city i in year t, $Flood_{i,t-s}$ is a dummy equal to one if at least one flood with a severity indicator of 1.5 or higher occurred in year $t-s$ for s = 1, 2, … up to 10; $city_t$ is city fixed effect, and $Year_t$ is year fixed effects; e_{it} is error term. To account for spatial correlation, the standard errors were clustered by city, which is a more conservative approach than that taken in most of the literature.

Since the interest of this study is in how past flood experience influences the change in the number of facilities after a flood, a dummy variable was created, denoted as $Experience_i$, to distinguish between cities with more and fewer frequent floods between 1985 and 2001. $Experience_i$ equals one if city i experienced more than six floods with a severity indicator of 1 or higher between 1985 and 2001. Figure 1 shows that the number of flood events with a severity indicator is more than one that each city experienced between 1985 and 2001. Table 1 shows the frequency distribution for large floods. Regressions with this variable were estimated, which we interact with $Flood_{i,t-s}$ for all s:

$$\ln(Y_{it}) = \beta_0 + \sum_{s=1}^{10} \beta_{1s} flood_{i,t-s} \times experience_i + \sum_{s=1}^{10} \beta_{2s} flood_{i,t-s} + experience_i + city_i + year_t + e_{it}. \tag{2}$$

Table 2 summarizes the description of variables and data sources. Table 3 shows the descriptive statistics.

4. Results and discussion

4.1 The effects of floods on manufacturing sectors

Estimation without lags

Table 4 presents the results estimated using Equation (1) without lags of the flood dummy variable. Column 1 shows that when there was at least one flood with a severity indicator of 1.5 or higher, the value of shipment of manufactured goods decreases by 2.1%. Columns 2 and 3 show that the effects on the value of shipment per facility and the number of employees are not statistically significant. Column 4 shows that the total number of facilities decreased by 2.4%. The effects of floods vary depending on the size of facilities. Column 5 shows that the number of small-sized facilities decreased by 3.0%, while Column 6 shows that the effect on the number of mid-sized facilities was not statistically significant. Column 7 shows that the number of large-sized facilities increases by 3.1%.

Estimation with lags

Next, more flexible models with ten-year flood lags were considered to better understand how long the effect of floods persists. Table 5 presents the results from estimating Equation (1)—that is, testing the effects of large floods on manufacturing sectors up to ten years after the floods. Table 6 presents the cumulative effect of floods on flow variables such as shipments, shipments per facility, and the number of employees, calculated by summing the respective flood dummy variable and its lags.[2]

Column 1 of Table 5 shows that last year's negative effects on the value of shipment of manufactured goods disappear at $t-2$. Interestingly, after $t-3$, the coefficient was positive and statistically significant, which means that the value of shipments in flooded cities was higher than that in nonflooded cities. The cumulative effect, as shown in Column 1 of Table 6, is an increase of 21.3% and statistically significant. This illustrates the "buildback better"

[2] The number of facilities is a stock variable. The coefficient of a 10-year lagged flood variable indicates the long-run effect of floods.

dynamics, in which the shipment of manufactured products grows in cities affected by floods. Column 2 in Table 5 shows that the value of shipment per facility also increases after the floods and that the cumulative effect in Table 6 is an increase of 25.9% and statistically significant. Column 3 shows that there was no negative effect on the number of employees, and the cumulative effect in Table 6 was not statistically significant. This means that employment does not grow beyond the baseline.

Column 4 shows that the negative impact of flooding on the total number of facilities persists for two years. The impacts almost vanished three years after the events. Column 5 shows that the negative effect on the number of small-sized facilities persists up to five years after the floods. Column 6 shows that the effect on the number of mid-sized facilities is negative at $t-2$, $t-3$, $t-4$, and $t-9$. Column 7 shows that the effect on the number of large-sized facilities is positive and statistically significant at $t-1$ and $t-7$ to $t-10$.

The interpretation of these results is as follows. The small and mid-sized facilities disappeared, and the number of large-sized facilities increased due to new entry or absorption or merging into larger ones. Economies of scale resulting from an increase in large-sized facilities may increase the value of manufactured goods shipped per facility. That is why we can see the "build back better" dynamic.

4.2 The role of past flood experiences

Estimation without lags

To examine how past experiences of flooding affect the magnitude of damage, the speed of recovery, and the number of facilities, the flood dummy could interact with a dummy distinguishing between "frequently flooded cities" and "rarely flooded cities". The dummy variable equals 1 if a city has experienced more than six floods with a severity indicator of 1 or higher between 1985 and 2001. Table 7 presents the results where the flood dummy variable interacts with the experience dummy variable without lags.

Column 1 shows that the coefficient of the interaction between the experience dummy and the flood dummy on the value of shipments was negative, but Column 2 shows that the coefficient on the value of shipments per facility was not statistically significant. Column 3 shows that the interaction effect on employment was negative. Columns 4–7 show that the interaction effect on the number of facilities was negative because floods have a negative impact on the total number of facilities.

Columns 6 and 7 show that the numbers of mid-sized and large facilities increased in rarely flooded cities, while they decreased in frequently flooded cities. This suggests that there is a firm's adaptive behavior to flooding, where firms tend to move their facilities to rarely flooded cities and restart the business or new firms start their business in rarely flooded cities because they think that the frequently flooded cities in the past are more likely to flood again. Column 5 shows that the number of small-sized facilities decreases in both frequently and rarely flooded cities, indicating that there was no entry of new facilities in either frequently or rarely flooded cities one year after the floods. This result suggests that small facilities are more vulnerable to flooding than larger facilities regardless of past flood experience.

Estimation with lags

How long the damage persists in cities that experienced more than six floods during 1985–2001 was examined. Figure 2 illustrates the long-run effect of flooding on the total number of facilities in frequently and rarely flooded cities. Figure 3 compares the long-run effect on small, mid-sized, and large facilities between both frequently and rarely flooded cities. Figure 4 compares the long-run effect of flooding on shipments, shipments per facility, and the number of employees between both frequently and rarely flooded cities. The effect in frequently and rarely flooded cities is the same as $\beta_{1s} + \beta_{2s}$ and β_{2s} in Eq. (2), respectively. Both figures display 95% confidential intervals. Table 8 shows the cumulative effect of the flow variables (shipment, shipment per facilities, and employment). Table A-1 in the Appendix presents the results obtained when the flood dummy variable interacted with the experience dummy variable.

Figure 2 shows that in frequently flooded cities, the last year's floods adversely affect the total number of facilities, and the effect persists up to eight years after the floods. Nine years after the floods, the total number of facilities recovers. In rarely flooded cities, the negative effects persist for two years. Three years after the floods, the number of facilities recovers temporally, but it decreases again, and the negative trend continues even ten years after the floods. Frequently flooded cities take flood protection measures based on lessons learned in the past (Neumayer et al. (2014)), and thus, the number of facilities increases. This result is consistent with this mechanism.

The next step was to analyze whether the effects vary depending on the size of the facilities. The following hypothesis was formulated. Smaller facilities that cannot afford flood protection may go bankrupt due to flood damage. Even if they survive, it may be more efficient to move their facilities to less flooded areas rather than take flood protection measures. Conversely,, the number of large facilities may not change because they can afford to take flood countermeasures.

The upper part of Figure 3 shows that in the frequently flooded cities in the past, the number of small and mid-sized facilities decreases due to the last year's floods. The negative effects disappear until ten years after the floods in both small and mid-sized facilities. In other words, the numbers of small and mid-sized facilities recovers in the long run. On the other hand, the number of large facilities does not change due to the last year's floods and increased beginning seven years after the floods. The lower part of Figure 3 shows that the number of small facilities decreases, and the number of mid-sized and large facilities increases due to the last year's floods. Three years after flooding, the number of small facilities temporally recovered, but it decreased again at $t - 8$. The number of large facilities increased temporarily one year after the floods. After the second year, the effects are not statistically significant.

In summary, in frequently flooded cities, the numbers of small and mid-sized facilities recovers in the long run. In rarely flooded cities, these facilities temporarily recovers but decrease in the long run. This suggests that small and mid-sized facilities prefer to be located in frequently flooded cities because flood control measures would be well developed in those cities. Large facilities survived flooding even in rarely flooded cities where flood control measures were not well installed. This suggests that large facilities are resilient to flooding.

Next, the effect of shipments and employment was evaluated. The upper part of Figure 4 shows that in frequently flooded cities, shipments of manufactured goods and employment decrease from $t - 1$ to $t - 4$ because the number of small and mid-sized facilities decreased during that period. Five years after the floods, the effect disappears. On the other hand, shipments per facility do not change from $t - 1$ to $t - 6$; they increase from $t - 7$ to $t - 10$ (the coefficient was positive and statistically significant at the more than 90% confidence level). The interpretation of this result is as follows. As shown in the upper part of Figure 3, large facilities increase seven years after flooding. Thus, because economies of scale result from an increase in large-sized facilities, the value of manufactured goods shipped per facility increases. The lower part of Figure 4 shows that in rarely flooded cities, the last year's floods do not affect shipments. Three years after the floods, shipments and employment temporally increase. Then, they decrease ten years after the floods.

Table 8 shows that the cumulative effect on shipments and shipments per facility was not statistically significant in either frequently or rarely flooded cities. The cumulative effect on employment is – 31.3% and statistically significant in frequently flooded cities.

The experience of past floods did not affect the business activities of large-sized facilities, but it affected the business activities of small- and mid-sized facilities. In frequently flooded cities, their activity recovered to predisaster levels. In the rarely flooded cities, there was a long-term decline in their activities because small and mid-sized facilities probably need to revise their supply chains due to unexpected events. In addition, unexpected flooding had devastating effects on employment even ten years after the floods, which is a serious issue for the regional economy.

4.3 Alternative specifications of panel results

Equation (1) was estimated using the prefecture-specific year fixed effect instead of the year fixed effect. The result are presented in Table A-1 in the Appendix. Comparing the alternative specification result with the baseline results presented in Table 5, we can obtain the following three results. First, the results obtained for the small facilities were similar to the baseline results: the number of small facilities decreases one year after the floods, and the negative effects persist up to five years after the floods. Second, the results for the mid-sized facilities are slightly different from the baseline results: they decrease even 10 years after the floods using a year×prefecture fixed effect. Third, floods do not affect the number of large facilities, which was different from the baseline result that the number of large facilities increases seven years after floods. These results suggest that floods may have devastating effects on small and mid-sized facilities in the long run, while large facilities were resilient to flooding.

5. Conclusion

This study examined how large floods affect the value of shipments, employment, and the number of facilities in manufacturing sectors in the long run. To do this, a finite distributed-lag model of 10-year order was used with municipal-level data in Japan. The impact of flooding depending on the size of facilities and past flood experience was estimated. It was found the "build back better" dynamic in which shipments of manufactured goods grow in cities affected by floods, and we found that the number of small and mid-sized facilities decreases, while the number of large facilities increased after floods.

These results suggest two important insights for the adaptation behavior of manufacturing sectors. First, large facilities are resilient to flooding, while small and mid-sized facilities are vulnerable to flooding. Therefore, small facilities exit the affected areas and/or may be absorbed or merged into larger facilities after large floods. As a result, economies of scale resulting from small facility exit and an increase in large-sized facilities may increase the shipments of manufactured goods per facility. That was why the build back better dynamics were found.

Considering the experience of past flooding, the following results were obtained. Experience with past floods did not affect the business activities of large facilities. However, it affects the activities of small and mid-sized facilities. In frequently flooded cities, the business activity of small and mid-sized facilities recovered to predisaster levels. In the rarely flooded cities, however, there was a long-term decline in the business activities of small and mid-sized facilities. In addition, unexpected flooding had devastating effects on employment, which was a serious problem for the regional economy. Unexpected flooding may force firms to rethink their supply chains, delaying decisions on business continuity and delaying government responses such as the introduction of subsidies. The task of future research is to understand the mechanism by which the business activities of small and mid-sized facilities are negatively affected for an extended period following flooding in rarely flooded cities.

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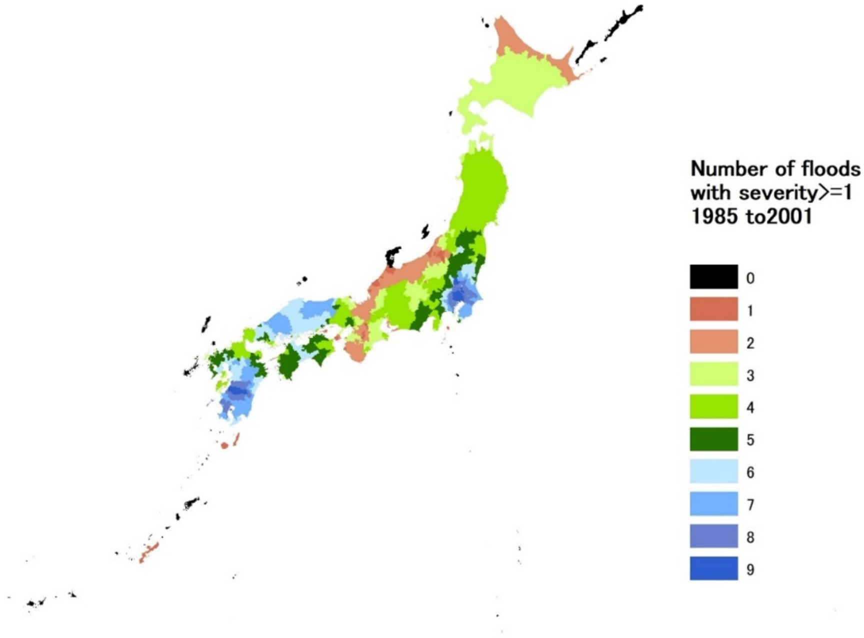


Figure 1. Flood frequency in 1985–2001

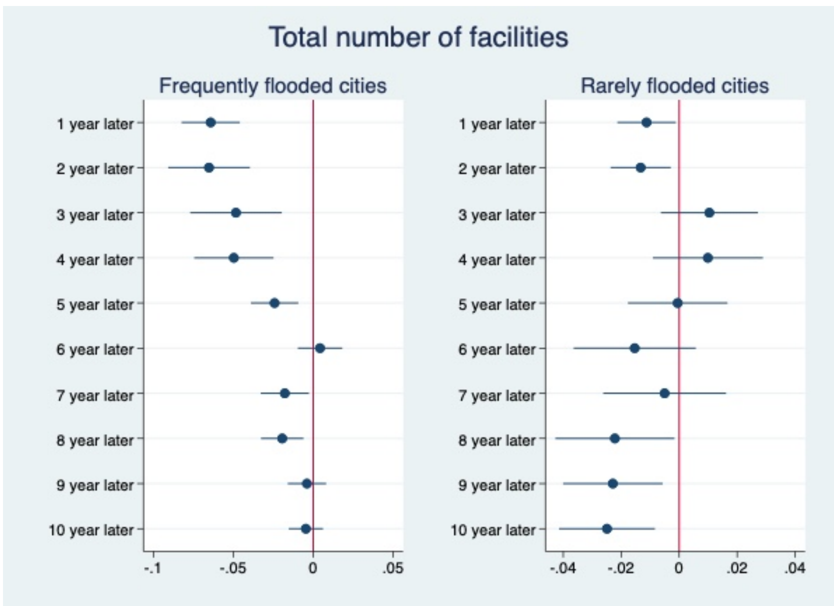
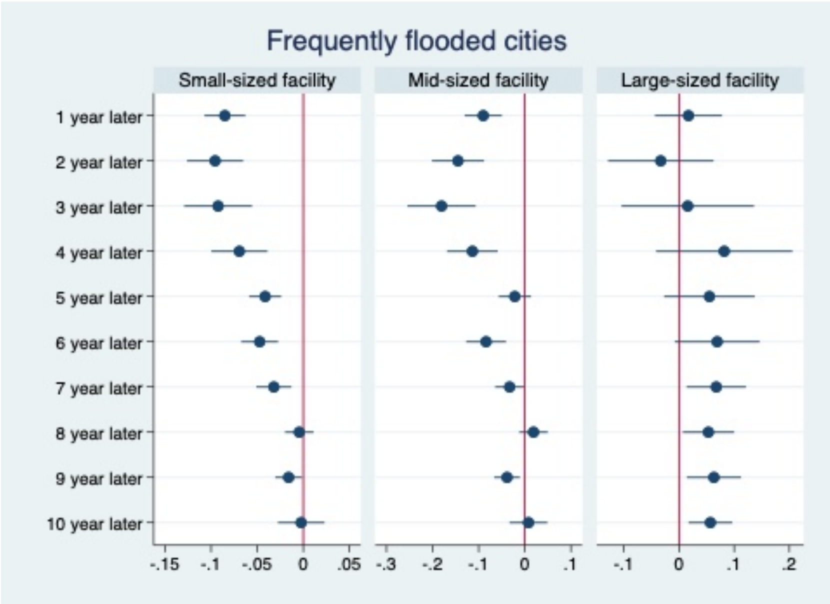


Figure 2. Long-run effects on the number of facilities: the role of experience



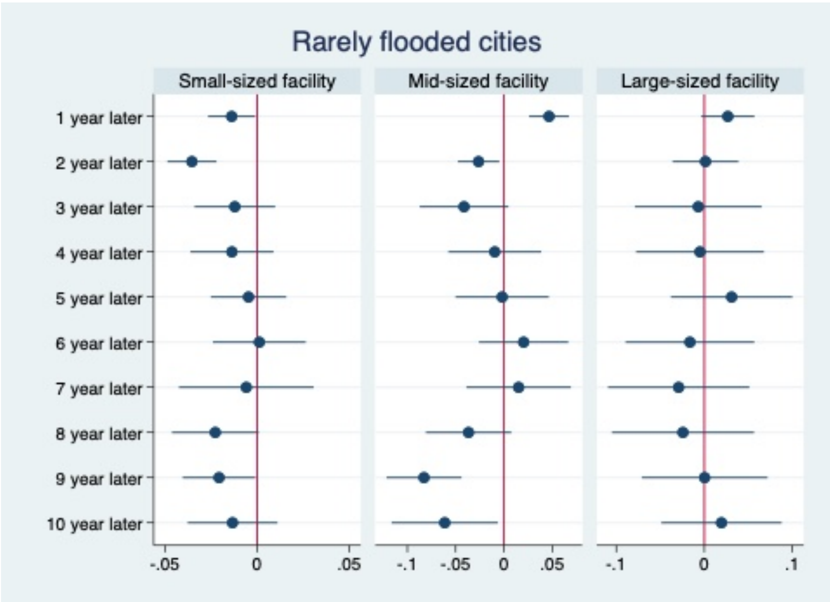


Figure 3. Heterogeneous effects of floods on facilities in frequently and rarely flooded cities

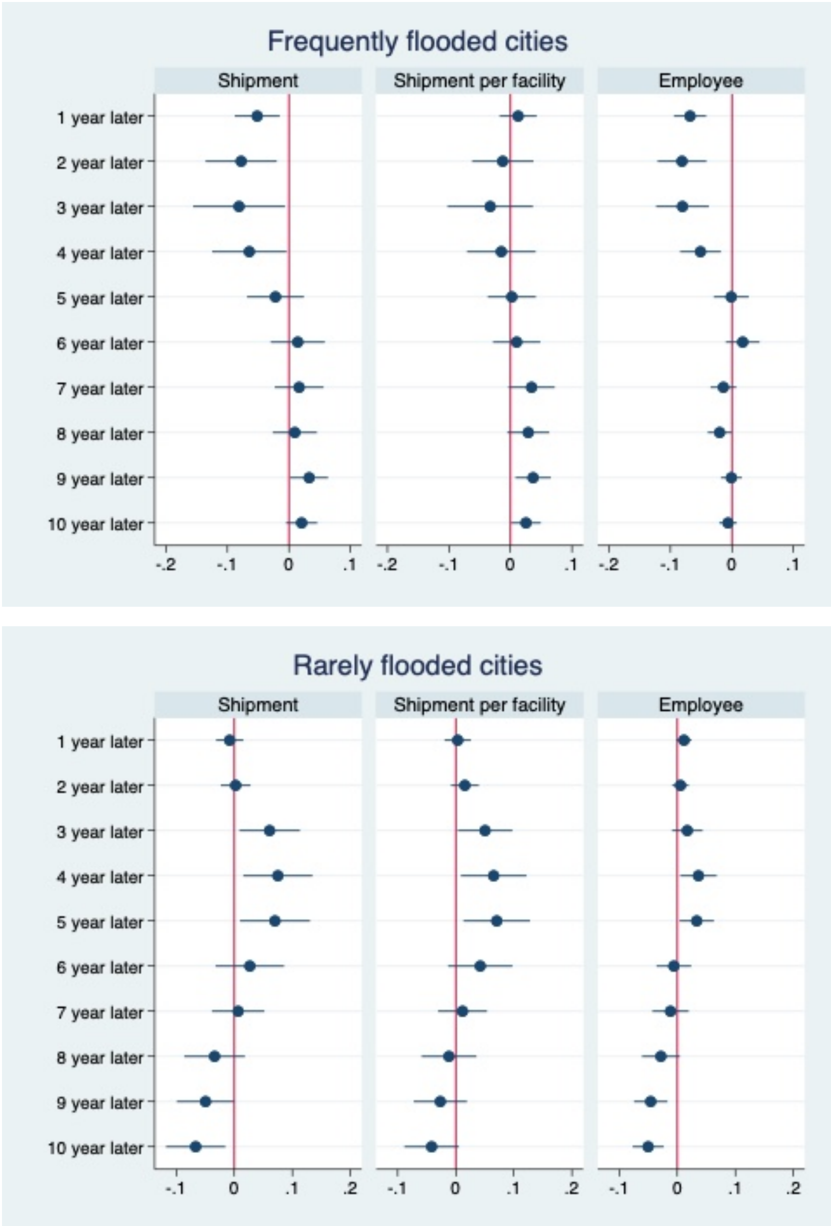


Figure 4. Long-run effects on shipments and employment in frequently and rarely flooded cities

Table 1. Flood frequencies and distribution of cities in 1985–2001

Number of floods	Number of cities	Percentage	Cumulative percentage
0	53	2.87	2.87
1	74	4.01	6.88
2	210	11.38	18.26
3	344	18.63	36.89
4	441	23.89	60.78
5	247	13.38	74.16
6	155	8.40	82.56
7	152	8.23	90.79
8	119	6.45	97.24
9	50	2.71	99.95
11	1	0.05	100.00
Total	1846	100.00	

Table 2. Descriptions of variables and data sources

Name	Description	Sources	Notes
$Shipment_{it}$	The value of shipment of manufactured goods in a city	METI	Flow variable
Shipment per $facility_{it}$	The value of shipment of manufactured goods per facility	METI	Obtained by dividing shipment by the total number of facilities. Flow variable
Employee	The number of employees in a city	METI	Flow variable
Total number of $facilities_{it}$	The total number of facilities in a city	METI	Stock variable
Number of small-sized $facilities_{it}$	The number of facilities with less than 10 employees in a city	METI	Stock variable
Number of mid-sized $facilities_{it}$	The number of facilities with 10–299 employees in a city	METI	Stock variable
Number of large-sized $facilities_{it}$	The number of facilities with 300 or more employees in a city	METI	Stock variable
$Flood_{i,t-s}$	Dummy variable representing city i's experience of flooding in year $t-s$	DFO	1 if at least more than one flood with severity indicator of 1.5 or higher occurred in year $t-s$
$Experience_i$	Dummy variable representing city i's past experience of large floods	DFO	1 if city i experienced more than six floods with severity indicator of 1 or higher between 1985 and 2001

Note: DFO, Dartmouth Flood Observatory; METI, Ministry of Economy, Trade and Industry, Japan

Table 3. Descriptive statistics

	Observations	Mean	S.D.	Min	Max
Full sample					
ln(Shipment)	15,561	15.22	1.89	8.64	21.00
ln(Shipment per facilities)	15,561	10.99	1.02	7.05	16.72
ln(Employee)	15,561	7.52	1.50	2.94	11.60
ln(Total number of facilities)	15,561	4.23	1.27	1.10	8.25
ln(Number of small-sized facilities)	15,525	3.95	1.28	0	8.17
ln(Number of mid-sized facilities)	14,355	2.73	1.25	0	7.28
ln(Number of large-sized facilities)	6,912	1.02	0.82	0	3.89
$\text{Flood}_{i,t-s}$	15,561	0.05	0.22	0	1
Experience_i	15,561	0.27	0.44	0	1
$\textit{Experience}_i = 1$					
ln(Shipment)	4,176	15.67	1.65	9.24	20.16
ln(Shipment per facilities)	4,176	11.15	0.98	7.85	14.41
ln(Employee)	4,176	7.87	1.29	3.56	10.68
ln(Total number of facilities)	4,176	4.52	1.13	1.39	7.83
ln(Number of small-sized facilities)	4,176	4.23	1.17	0	7.76
ln(Number of mid-sized facilities)	4,014	2.93	1.12	0	6.76
ln(Number of large-sized facilities)	2,106	1.04	0.806	0	3.09
$\text{Flood}_{i,t-s}$	4,176	0.04	0.20	0	1
$\textit{Experience}_i = 0$					
ln(Shipment)	11,385	15.06	1.95	8.64	21.00
ln(Shipment per facilities)	11,385	10.94	1.03	7.05	16.72
ln(Employee)	11,385	7.39	1.56	2.94	11.60
ln(Total number of facilities)	11,385	4.12	1.31	1.10	8.25
ln(Number of small-sized facilities)	11,349	3.86	1.31	0	8.17
ln(Number of mid-sized facilities)	10,341	2.65	1.28	0	7.28
ln(Number of large-sized facilities)	4,806	1.01	0.82	0	3.89
$\text{Flood}_{i,t-s}$	11,385	0.06	0.23	0	1

Note: Observations in small, mid, and large-sized facilities are smaller than that in the total facilities because there are some cities that have no small, mid, and large-sized facilities.

Table 4. Effects of floods

	(1) Shipment	(2) Shipment per facility	(3) Employee	(4) Total number of facilities	(5) Number of small-sized facilities	(6) Number of mid-sized facilities	(7) Number of large-sized facilities
$Flood_{i,t-1}$	-0.0214*	0.00272	-0.00706	-0.0241***	-0.0290***	0.0114	0.0322**
	(0.0111)	(0.0103)	(0.00644)	(0.00480)	(0.00595)	(0.00993)	(0.0152)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,561	15,561	15,561	15,561	15,525	14,355	6,912
Adjusted within R^2	0.000393	6.43×10^{-5}	7.65×10^{-5}	0.00287	0.00183	6.07×10^{-5}	0.000761

Notes: Robust standard errors, clustered by city, in parentheses. *** denotes p<0.01, ** denotes p<0.05, and * denotes p<0.1. Observations in columns of (5)-(7) are smaller than the others because some cities have no small-sized, or mid-sized, or large-sized facilities.

Table 5. Model with lags

	(1) Shipment	(2) Shipment per facility	(3) Employee	(4) Total number of facilities	(5) Number of small-sized facilities	(6) Number of mid-sized facilities	(7) Number of large-sized facilities
$Flood_{i,t-1}$	-0.0232**	0.000721	-0.00792	-0.0239***	-0.0264***	0.0171*	0.0312**
	(0.0109)	(0.0101)	(0.00629)	(0.00471)	(0.00570)	(0.00953)	(0.0153)
$Flood_{i,t-2}$	-0.0117	0.00803	-0.00721	-0.0197***	-0.0416***	-0.0342***	-0.0157
	(0.0122)	(0.0111)	(0.00727)	(0.00517)	(0.00642)	(0.0103)	(0.0203)
$Flood_{i,t-3}$	0.0370*	0.0292	0.0122	0.00781	-0.0207**	-0.0537***	0.0119
	(0.0210)	(0.0190)	(0.0105)	(0.00706)	(0.00894)	(0.0179)	(0.0345)
$Flood_{i,t-4}$	0.0360	0.0403*	0.0153	-0.00434	-0.0279***	-0.0438**	0.0350
	(0.0236)	(0.0218)	(0.0126)	(0.00773)	(0.00896)	(0.0186)	(0.0352)
$Flood_{i,t-5}$	0.0385*	0.0475**	0.0222**	-0.00899	-0.0189***	-0.0108	0.0303
	(0.0206)	(0.0193)	(0.0107)	(0.00576)	(0.00659)	(0.0154)	(0.0286)
$Flood_{i,t-6}$	0.0483**	0.0450**	0.0259**	0.00337	0.000188	0.0222	0.0242
	(0.0225)	(0.0206)	(0.0117)	(0.00776)	(0.00831)	(0.0167)	(0.0288)
$Flood_{i,t-7}$	0.0289*	0.0291**	0.00626	-0.000181	-0.00482	0.0129	0.0548**
	(0.0150)	(0.0134)	(0.00938)	(0.00641)	(0.00858)	(0.0135)	(0.0236)
$Flood_{i,t-8}$	0.0148	0.0209	-0.000667	-0.00613	-0.000716	0.0184	0.0505**
	(0.0148)	(0.0135)	(0.00860)	(0.00559)	(0.00684)	(0.0139)	(0.0218)
$Flood_{i,t-9}$	0.0279**	0.0248**	0.00560	0.00313	-0.00316	-0.0268**	0.0501**
	(0.0137)	(0.0121)	(0.00833)	(0.00551)	(0.00576)	(0.0109)	(0.0233)
$Flood_{i,t-10}$	0.0164	0.0134	0.000492	0.00301	0.0108	0.00712	0.0590***
	(0.0121)	(0.0107)	(0.00706)	(0.00490)	(0.00931)	(0.0164)	(0.0199)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,561	15,561	15,561	15,561	15,525	14,355	6,912
Adjusted within R^2	0.00166	0.00128	0.000649	0.00415	0.00480	0.00294	0.00403

Notes: Robust standard errors, clustered by city, in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.1$.

Table 6. Cumulative effects of floods on shipments and employment

	(1) Shipment	(2) Shipment per facility	(3) Employee
Cumulative effects	0.213**	0.259***	0.0722
	(0.103)	(0.0918)	(0.0618)

Notes: Cumulative effects are calculated by summing the coefficient of flood variable and its lags. Robust standard errors, clustered by city, in parentheses. *** denotes $p<0.01$, ** denotes $p<0.05$, and * denotes $p<0.1$.

Table 7. Effects of floods: the role of past flood experiences

	(1) Shipment	(2) Shipment per firm	(3) Employee	(4) Total number of facilities	(5) Number of small-sized facilities	(6) Number of mid-sized facilities	(7) Number of large-sized facilities
$Flood_{i,t-1}$	-0.00865	0.00551	0.00841	-0.0142***	-0.0164**	0.0384***	0.0440**
	(0.0128)	(0.0123)	(0.00695)	(0.00528)	(0.00656)	(0.0104)	(0.0171)
$Flood_{i,t-1}\times$	-0.0616***	-0.0135	-0.0748***	-0.0481***	-0.0610***	-0.129***	-0.0641*
$Experience_i$	(0.0222)	(0.0176)	(0.0154)	(0.0108)	(0.0124)	(0.0228)	(0.0342)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,561	15,561	15,561	15,561	15,525	14,355	6,912
Adjusted within R^2	0.00103	0.0001	0.00306	0.00494	0.00329	0.00333	0.00123

Notes: Robust standard errors, clustered by city, in parentheses. *** denotes p<0.01, ** denotes p<0.05, and * denotes p<0.1. $Experience_i = 1$ if the total number of floods with a severity indicator of 1 or higher each city experienced during 1985–2001 is more than six.

Table 8. Cumulative effects of floods on shipment and employment in the frequently and rarely flooded cities

	(1) Shipment	(2) Shipment per facility	(3) Employee
Frequently flooded cities	-0.196	0.109	-0.313***
	(0.174)	(0.161)	(0.0998)
Rarely flooded cities	0.0650	0.152	-0.0388
	(0.148)	(0.131)	(0.0995)

Notes: Cumulative effects are calculated by summing $\beta_{1s} + \beta_{2s}$ or β_{2s}. Robust standard errors, clustered by city, in parentheses. *** denotes p<0.01, ** denotes p<0.05, and * denotes p<0.1.

Appendix

Table A-1. Long-run effects of floods: the role of past flood experiences

	(1) Shipment	(2) Shipment per firm	(3) Employee	(4) Total number of facilities	(5) Number of small-sized facilities	(6) Number of mid-sized facilities	(7) Number of large-sized facilities
$Flood_{i,t-1}$	-0.0442*	0.0163	-0.0886***	-0.0605***	-0.0788***	-0.144***	-0.0183
× $Experience_i$	(0.0233)	(0.0203)	(0.0160)	(0.0111)	(0.0135)	(0.0248)	(0.0405)
$Flood_{i,t-2}$	-0.0907***	-0.0330	-0.0977***	-0.0577***	-0.0667***	-0.120***	-0.0257
× $Experience_i$	(0.0335)	(0.0292)	(0.0227)	(0.0146)	(0.0177)	(0.0328)	(0.0581)
$Flood_{i,t-3}$	-0.148***	-0.0808*	-0.104***	-0.0671***	-0.0865***	-0.122***	0.0107
× $Experience_i$	(0.0487)	(0.0446)	(0.0274)	(0.0175)	(0.0227)	(0.0443)	(0.0790)
$Flood_{i,t-4}$	-0.134***	-0.0715*	-0.0836***	-0.0624***	-0.0568***	-0.0916**	0.0230
× $Experience_i$	(0.0453)	(0.0421)	(0.0246)	(0.0169)	(0.0203)	(0.0382)	(0.0780)
$Flood_{i,t-5}$	-0.0894**	-0.0655*	-0.0349	-0.0239**	-0.0351**	-0.0137	-0.0129
× $Experience_i$	(0.0399)	(0.0367)	(0.0218)	(0.0117)	(0.0139)	(0.0312)	(0.0590)
$Flood_{i,t-6}$	-0.00376	-0.0302	0.0308	0.0264*	-0.0440**	-0.106***	0.0933
× $Experience_i$	(0.0397)	(0.0364)	(0.0223)	(0.0135)	(0.0174)	(0.0346)	(0.0640)
$Flood_{i,t-7}$	0.0230	0.0355	0.000661	-0.0126	-0.0284	-0.0556	0.132**
× $Experience_i$	(0.0311)	(0.0287)	(0.0203)	(0.0136)	(0.0216)	(0.0344)	(0.0540)
$Flood_{i,t-8}$	0.0519	0.0475	0.0124	0.00442	0.0209	0.0675**	0.0839
× $Experience_i$	(0.0333)	(0.0305)	(0.0203)	(0.0131)	(0.0149)	(0.0287)	(0.0519)
$Flood_{i,t-9}$	0.0855***	0.0676**	0.0456**	0.0179	0.00367	0.0481*	0.0109
× $Experience_i$	(0.0306)	(0.0284)	(0.0179)	(0.0111)	(0.0128)	(0.0257)	(0.0486)
$Flood_{i,t-10}$	0.0885***	0.0714**	0.0448***	0.0171	0.00775	0.0693**	0.0204
× $Experience_i$	(0.0304)	(0.0280)	(0.0162)	(0.0105)	(0.0186)	(0.0352)	(0.0456)
$Flood_{i,t-1}$	-0.0116	-0.000670	0.0112*	-0.0109**	-0.0118*	0.0490***	0.0339**
	(0.0124)	(0.0120)	(0.00678)	(0.00528)	(0.00671)	(0.0109)	(0.0170)
$Flood_{i,t-2}$	0.00588	0.0184	0.00688	-0.0125**	-0.0351***	-0.0271**	-0.00659
	(0.0132)	(0.0124)	(0.00741)	(0.00542)	(0.00698)	(0.0113)	(0.0213)
$Flood_{i,t-3}$	0.0656**	0.0521**	0.0202	0.0135	-0.0102	-0.0424*	-0.00705
	(0.0280)	(0.0250)	(0.0142)	(0.00910)	(0.0119)	(0.0247)	(0.0450)
$Flood_{i,t-4}$	0.0730**	0.0573*	0.0401**	0.0157	-0.00931	-0.0115	0.0148
	(0.0313)	(0.0295)	(0.0167)	(0.00996)	(0.0120)	(0.0258)	(0.0434)
$Flood_{i,t-5}$	0.0697**	0.0708**	0.0334**	-0.00112	-0.00681	-0.00756	0.0307
	(0.0319)	(0.0305)	(0.0157)	(0.00904)	(0.0107)	(0.0254)	(0.0421)
$Flood_{i,t-6}$	0.0196	0.0395	-0.00992	-0.0198*	0.000794	0.0259	-0.0273
	(0.0310)	(0.0292)	(0.0157)	(0.0111)	(0.0135)	(0.0248)	(0.0414)
$Flood_{i,t-7}$	-0.00139	0.00294	-0.0141	-0.00433	-7.19e-05	0.0234	-0.0435
	(0.0235)	(0.0215)	(0.0166)	(0.0111)	(0.0194)	(0.0298)	(0.0456)
$Flood_{i,t-8}$	-0.0370	-0.0146	-0.0292*	-0.0224**	-0.0260**	-0.0454*	-0.0159
	(0.0277)	(0.0250)	(0.0172)	(0.0110)	(0.0125)	(0.0233)	(0.0458)
$Flood_{i,t-9}$	-0.0525**	-0.0306	-0.0461***	-0.0219**	-0.0194*	-0.0841***	0.0379
	(0.0264)	(0.0244)	(0.0151)	(0.00909)	(0.0105)	(0.0212)	(0.0413)
$Flood_{i,t-10}$	-0.0663**	-0.0430*	-0.0512***	-0.0233***	-0.00907	-0.0615**	0.0350
	(0.0281)	(0.0257)	(0.0143)	(0.00894)	(0.0133)	(0.0277)	(0.0404)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Observations	15,561	15,561	15,561	15,561	15,525	14,355	6,912
Adjusted within R^2	0.00800	0.00381	0.0118	0.0113	0.00839	0.0109	0.00556

Notes: Robust standard errors, clustered by city, in parentheses. *** denotes p<0.01, ** denotes p<0.05, and * denotes p<0.1. Experience$_i$ = 1 if the total number of floods with a severity indicator of 1 or higher each city experienced during 1985–2001 is more than six.

Table A-2. Long-run effects of floods: year*prefecture FE

	(1) Shipment	(2) Shipment per facility	(3) Employee	(4) Total number of facilities	(5) Number of small-sized facilities	(6) Number of mid-sized facilities	(7) Number of large-sized facilities
Flood$_{i,t-1}$	-0.0258*	-0.0101	-0.0130	-0.0156**	-0.0110	0.0250*	0.000596
	(0.0145)	(0.0145)	(0.00884)	(0.00660)	(0.00793)	(0.0143)	(0.0225)
Flood$_{i,t-2}$	-0.0152	0.00678	-0.0172	-0.0220**	-0.0299***	-0.0383**	-0.0307
	(0.0211)	(0.0198)	(0.0130)	(0.00906)	(0.0107)	(0.0171)	(0.0347)
Flood$_{i,t-3}$	0.0151	0.0249	-0.00531	-0.00988	-0.0297**	-0.0577**	-0.0179
	(0.0264)	(0.0239)	(0.0149)	(0.00968)	(0.0118)	(0.0240)	(0.0438)
Flood$_{i,t-4}$	0.0115	0.0310	-0.0154	-0.0195**	-0.0332***	-0.0623***	0.00918
	(0.0277)	(0.0252)	(0.0155)	(0.00979)	(0.0112)	(0.0231)	(0.0423)
Flood$_{i,t-5}$	0.0160	0.0306	-0.00192	-0.0146*	-0.0162*	-0.0158	0.00199
	(0.0247)	(0.0232)	(0.0133)	(0.00765)	(0.00851)	(0.0190)	(0.0330)
Flood$_{i,t-6}$	-0.00867	-0.00487	-0.00702	-0.00380	-0.00330	-0.0187	-0.0351
	(0.0295)	(0.0281)	(0.0159)	(0.00917)	(0.00994)	(0.0230)	(0.0388)
Flood$_{i,t-7}$	-0.0205	-0.0104	-0.0223	-0.0101	-0.00769	-0.0334	-0.0136
	(0.0246)	(0.0233)	(0.0151)	(0.00923)	(0.0109)	(0.0217)	(0.0423)
Flood$_{i,t-8}$	-0.0339	-0.0109	-0.0297**	-0.0231***	-0.00463	0.00288	0.0202
	(0.0228)	(0.0221)	(0.0131)	(0.00821)	(0.0117)	(0.0224)	(0.0410)
Flood$_{i,t-9}$	-0.0340	-0.0276	-0.0106	-0.00639	-0.00905	-0.0746***	0.0458
	(0.0210)	(0.0207)	(0.0120)	(0.00777)	(0.00869)	(0.0175)	(0.0368)
Flood$_{i,t-10}$	-0.0322*	-0.0252	-0.0181*	-0.00698	-0.00356	-0.0603***	0.0454
	(0.0173)	(0.0165)	(0.00997)	(0.00651)	(0.0106)	(0.0209)	(0.0310)
Year*pref. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,561	15,561	15,561	15,561	15,525	14,355	6,912
Adjusted Within R^2	0.0006	0.0004	0.0005	0.001	0.0005	0.0028	0.000

Notes: Robust standard errors, clustered by city, in parentheses. *** denotes p < 0.01, ** denotes p < 0.05, and * denotes p < 0.1.