O-007

The economic impact of heavy rain stream on supply chain

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1.Introduction

Modern global climate change is already far from negligible issue, and a huge risk for all lives on the earth and the societal activities of human. The changes can trigger disasters which damage the society, especially the economy. Since tackling the global climate change requires solving conflicts in society and economy, regionally and internationally, it is beneficial to estimate the economic risk of the global climate change to examine the issue objectively.

Although the global climate change is the long-term issue and there is literature contingent to its long-term economic change, disasters are extreme events and the economic changes occur in short terms. Therefore, to estimate the economic loss of the disaster, we need to examine the aspect of the economy that changes temporally in the short term.

When a disaster occurs, directly affected firms reduce production in a particular region, the suppliers of firms directly affected by the shock need to reduce their production because of a lack of demand, and their customers also need to reduce production because of a shortage of material, parts, or components. As a result, a regional shock can lead to a substantial indirect effect, often more substantial than the direct effect of the shock itself , and hence large fluctuations across the economy. Therefore, although the disaster is regionally limited, we have to consider the large economic system including the impacted area and the related economic actors to estimate the economic loss of the disaster.

Although the global climate change causes diverse disasters, ones of serious issues are excess of precipitation or the sea level rise, which causes flood and related disasters such as sediment disasters. Especially, in Japan, the frequency of the heavy rain is increasing. Unlike other types of major disasters, such as earthquake or tsunami, the heavy rain occurs in a stream, i.e., at multiple distant places in a short period, and causes multiple floods and related disasters. If we only consider the damage of buildings or infrastructures, the total of the damage caused by the multiple heavy rain is a simple summation of each different places and times, and we do not need to consider the relationships between the the rains. However, if we estimate the loss of economic system entirely, we cannot ignore the relationships between the rains because firms are connected through supply chains. Moreover, firms in distant places tend to have different functions [1, 2] in supply chains. Therefore, it would be possible to worsen the total damage to the economy because of the interaction of the damages given to different economic components.

To estimate the damage of the shock to the economy, we cannot ignore the complexity of the system. Despite recent findings in the network science literature that the structure of networks significantly influences diffusion, empirical studies of diffusion through supply chains have not fully incorporated the complex nature of the networks among firms. A notable feature of the network complexity is scale-free property: there are a few giant hubs linked with an extremely large number of firms, and thus most firms are linked indirectly by a few steps through the hubs. If the complexity of actual networks is not fully incorporated, the analysis of propagation of shocks through supply chains is most likely to underestimate the size and persistence of the propagation. However, some ealier works rely on inter-industry analysis based on input–output (IO) tables, ignoring firm-level networks. Others adopt computable general equilibrium models that assume homogeneous firms in each industry, disregarding substantial variation in the number of links across firms.

On the other hand, several recent studies have incorporated inter-firm supply-chain relations into their analyses. Some of them employ hypothetical networks of firms, whose network complexity may be quite different from that of actual networks. Others incorporate actual supply-chain networks of firms and evaluate the damage of the Great East Japan Earthquake and the Nankai Trough Earthquake [3]. However, they consider the damage at once, not the multiple damages on supply chains in a short term.

To fill the above research gap, the present study uses the actual supply-chain relations of 1.6 million firms in Japan and apply an agent-based model in which heterogeneous firms are linked through supply chains to the supply-chain data. Furthermore, we estimate the multiple heavy rains in July 2020 in Japan as a source of negative economic shocks in a short period. Then, we examine virtual scenarios so that we can see the characteristics of the economic shocks triggered by a series of negative shocks.

2.Method

2.1.Supply-chain Data

The data used in this study are taken from the Company Information Database and Company Linkage Database compiled by Tokyo Shoko Research (TSR), one of the largest credit research companies in Japan. The former database includes information about the attributes of each firm, including the location, industry, sales, and number of employees, and the latter includes the major customers and suppliers of each firm. Due to availability, we use the data on firm attributes and supply chains from 2016. The number of firms in the data is 1,668,567 and the number of supply-chain links is 5,943,073. Hence, our data identify the major supply chains of most firms in Japan, although they lack information about supply-chain links with foreign entities.

In the TSR data, the maximum number of suppliers and clients reported by each firm is 24. However, when we consider supplier-client relations running in the opposite direction, each firm can have more than 24 suppliers or 24 clients. Since the TSR data include the address of the headquarters of each firm, we can obtain the location of them.

Because the transaction value of each supply-chain tie is not available in the data, we estimate sales from a supplier to each of its customers and consumers using the total sales of the supplier and the 2015 Input-Output (IO) Tables for Japan. In this estimation process, we drop firms without any sales information. Accordingly, the number of firms in our final analysis is 966,627 and the number of links is 3,544,343. Although the firms in the TSR data are classified into 1,460 industries according to the Japan Standard Industrial Classification, we simplify this into the 187 industries classified in the IO tables. To estimate the transaction value, first, we divide each supplier's sales among its clients in proportion to the clients' sales to create a tentative sales value. Second, we refer to the IO table of Japan in 2015 to transform the tentative values so that the total volume corresponds to GDP. Specifically, we aggregate the tentative values at the firm-pair level to create the total sales for each pair of industrial sectors. We then divide the total sales for each industrial sector pair by the transaction values for the corresponding pair in the IO tables. The ratio is then used to adjust the transaction values between firms. The final consumption of each industrial sector is assigned to all firms in the sector using their sales as weights.

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2.2.Heavy rain stream in July 2020 in Japan

The seasonal rain front in 2020 stretched from China to the eastern area of Japan and stagnated from 3rd July. As results, almost all areas in Japan had precipitation at record pace. In particular, Kyusyu area (the western island of Japan) had severe rainstorm from 4th to 7th July and Gifu prefecture had the one from 6th to 8th July. Japan Meteorological Agency issued a special heavy alert warning for Kumamoto, Kagoshima, Fukuoka, Saga, Nagano, Gifu, and Nagano prefectures. After 8th July, the rain front stagnated until the end of July. Many areas in Japan renewed the record of precipitation per 24, 48, and 72 hours.

As meteorological consequences of the severe precipitation, floods and sediment disasters occurred. Floods occurred in eight rivers managed by the national government and 194 rivers managed by the regional governments. In total, area of 13,000 ha was flooded. In addition, 932 cases of sediment disasters were also reported. Cabinet Office of Japanese government tallied the casualties and the dwelling house damage by municipality. There are 241 municipalities with the casuality and the damage. We tallied numbers of the dwelling house damage by prefectures. Since the dates are not given to the aggregated count data by Cabinet Office, we combine it with the precipitation record by Japan Meteorological Agency. The visualization on the map is Figure 1. The municipality is coloured if it has more than 0 case. The colour indicate the date of the rain. The figure indicates that a lot of areas were damaged by the floods and the sediment disasters and that the areas are diverse. Since there is no data indicating the number of damaged firms, we utilize this data to create damaged firm data. The detailed procedure is indicated in Section 2.4.

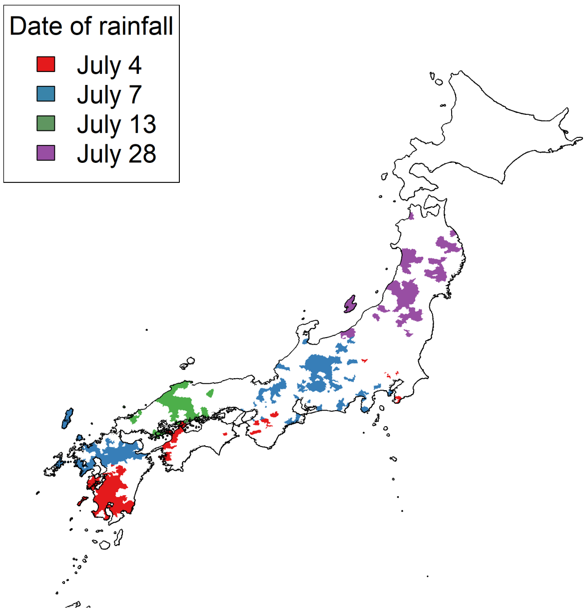

Figure 1: Rainfall date and damaged areas. Coloured areas are municipalities with the report of the dwelling house damage. Each colour indicates the date of the rainfall.

2.3.Model

We employ the dynamic agent-based model of Inoue and Todo [3], an extension of Hallegatte's [4] model, which assumes that supply chains are at the firm level. In the model, each firm utilises the inputs purchased from other firms to produce an output and sells it to other firms and consumers. Firms in the same industry are assumed to produce the same output. Supply chains are predetermined, and do not change over time in the following two respects. First, each firm utilises a firm-specific set of input varieties and does not change the input set over time. Second, each firm is linked with fixed suppliers and customers and cannot be linked with any new firm over time, even after a supply-chain disruption. Accordingly, our analysis focuses on short-term changes in production. Furthermore, we assume that each firm keeps inventories of each input at a level randomly determined from the Poisson distribution.

Following the procedure of Inoue and Todo [3], the parameter values are calibrated from the case of the Great East Japan earthquake. Those parameters are n (the mean number of days for which inventories of inputs are targeted to hold), σ (the number of days without recovery after the earthquake), and γ (the recovery rate). By calibration, we set these parameters as $n = 10$, $\sigma = 11$, and $\gamma = 0.033$, respectively. Note that the values are different from the calibration in [3]. This is because the model is modified and the calibrations are conducted for the model.

Since the model has parameters, they should be calibrated. Following [3], we calibrate the model by using the case of the 2011 Japan earthquake. Particularly, we estimate the value of three parameters: n (the mean number of days for which inventories of inputs are targeted to hold), σ (the number of days without recovery after the earthquake), and γ (the recovery rate). We then simulate how the value of production less the total value of the intermediates used for production, i.e., the value added, of all the firms in the economy changes over time and calculate the daily summation. For each set of parameter values, we carry out 30 simulations, randomly changing firms initially damaged, and take the average of the simulated value added. The average of the total direct (initial) losses in value added is 1.7 trillion yen. The parameters of the model are calibrated by minimizing the sum of the squared differences between the simulated and actual value added. Because total value added, or gross domestic product (GDP), is available only quarterly, we estimate average value added per day for each month from the industrial production index available monthly and value added taken from the IO tables. The parameter search ranges from 1 to 20 for n, from 0 to 20 for σ, and from 0.005 to 0.100 for γ. The step sizes are 1, 1, and 0.005, respectively. Therefore, combinations of the 8,400 sets composed of the three parameters are tested. This process leads to $n = 9$, $\sigma = 6$, and $\gamma = 0.025$.

When a firm is affected by the disaster directly, both its upstream and downstream of the firm are affected. On the one hand, the firm's demand for parts and components from its suppliers immediately declines, and thus suppliers have to shrink their production. Because demand for the products of suppliers' suppliers also declines, the negative effect of the shock propagates upstream. On the other hand, the supply of products from the directly damaged firm to its customer firms declines. Therefore, one way for customer firms to maintain the current level of production is to use their inventories of inputs. Alternatively, customers can procure inputs from other suppliers in the same industry that were already connected before the disaster, provided these suppliers have additional production capacity. If the inventories and inputs from substitute suppliers are insufficient, customers have to shrink their production because of a shortage of inputs. Accordingly, the effect of the disaster propagates downstream through supply chains. Such downstream propagation is likely to be slower than upstream propagation because of the inventory buffer and input substitution.

As time proceeds, directly damaged firms recover their production capacity and the demand and supply from the

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firms also return. The recovery rate is for daily. Basically, the daily recovery rate is constant and common in all damaged firms. However, it is deteriorated if the trade partners of the focal firm are also damaged.

Without any direct damage, the model keeps the initial production level, i.e., the system shows no direct and indirect damage. After direct damages are given, the simulation estimates the indirect damage based on the model.

2.4.Simulation Procedure

Estimation of actual event Based on the model described in Section 2.3, the simulation calculates the propagation of the direct damage. Although the national government has implemented several aids for the damaged firms, there is no data about how many damaged firms there are in the areas and obviously no data about which firms are damaged. Therefore, we estimate the share of damaged firms in the impacted areas and create sets of directly damaged firms based on the share. To obtain the share of affected firms, we utilize the dwelling house damage as the proxy of the directly damaged firm. There are five types of damage: complete, partial, and some destruction, and flood above floor and under floor. We obtain the rate of each damage type in proportion to the number of dwelling house, i.e., the number of the case over the number of the dwelling house. Then, we apply the rate to the number of firms in the affected area, which means we randomly determine firms directly damaged by the flood and sediment disaster. If a firm is chosen as an initially damaged firm, its production capacity ($P\mathrm{cap}_i$) decreases by 1.0 for complete, 0.5 for partial, and 0.2 for some destruction, respectively. We follow the reduction rate indicated in [3]. In the same way, it decreases by 1.0 for above floor flood and 0.5 for below floor flood. Since a set of directly damaged firms is randomly created, the estimation has a variance. Therefore, we run 100 Monte-Carlo simulations to obtain an estimation.

Virtual scenarios to evaluate actual event By creating different scenarios contrast to the actual event and comparing the results of them with the actual result, we reveal characteristics of the economic loss by the actual event.

First scenario is about the areas vulnerable to heavy rains. We examine which areas are economically subject to the heavy rain. Intuitively, if an area is economically important, it would probably be highly protected from the disaster, and vice versa. To examine this question, we randomly choose firms from the entire dataset, i.e., firms in any areas in Japan. However, the number of the affected firms, the damage magnitude, and the date of the event are the same as the actual event. Therefore, only the firms are randomly changed in the actual event. If the above hypothesis is incorrect, i.e., areas which are subject to the heavy rain has no difference in economic importance, the estimated loss of the virtual scenario is not statistically different from the actual event. We call this scenario 'Firm shuffle' hereafter.

Second scenario is about the firms vulnerablity to heavy rains. In 'Firm shuffle', we compare the damaged areas with the overall areas. We can further compare the vulnerability of firms in the damaged firms. If a firm is economically more important, it would probably be protected more from the disaster than economically less important firms. To examine this question, we randomly shuffle the damage of firms in the actual scenario. Therefore, in the dataset, the firms IDs are randomly shuffled, i.e. the damage magnitude and the date of the event are preserved. If the above hypothesis is incorrect, i.e., firms' vulnerability to the heavy rain is independent of firms' economic importance, the estimated loss of the virtual scenario is not statistically different from the actual event. We call this scenario 'Damaged firm shuffle' hereafter.

A further question is simultaneousness. Multiple heavy rains often occur in the short period in different places, the damages on the economy may remain or interact with each other. As a result, it may cause more serious economic losses. To see such interactions, we change the date of the actual scenario so that all damages to firms happen at the same day (the first day). If the above hypothesis is incorrect, i.e., there is no difference when the heavy rains hit the areas at the same time, the estimated loss of the virtual scenario is not statistically different from the actual event. We call this scenario 'Damage at once' hereafter.

3.Results

Figure 2 indicates the temporal change of the daily value added (VA) loss for the actual and virtual scenarios. Note that the day 0 indicates 3rd July in the actual scenario. Although the heavy rains occurred in July, the peaks of the daily losses come later. The peaks of 'Firm shuffle' and 'Damaged firm shuffle' scenarios are more clearer than Actual and Damage at once scenarios, but it seems that the peaks are indeed around day 50. This delayed peaks after shocks mean that the daily losses expands after the shocks for all scenarios because of the propagation into the supply chains. After the peaks, the daily value added losses decay into almost zero after 200 days later from the beginning of the rains.

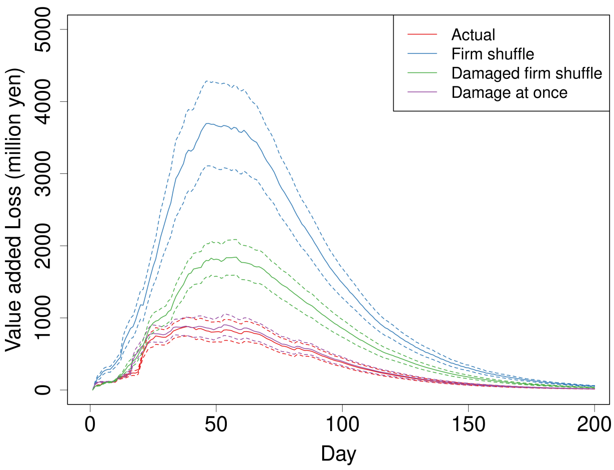

Figure 2: Temporal change of VA loss. Note that the value added loss is daily. The lines show the average of VA losses of 100 Monte Carlo runs for each scenario. The dashed lines show the standard errors.

Although the comparisons between the scenarios can roughly be done with Figure 2, Figure 3 indicates the total VA losses of the scenarios. The total VA losses are summations of the daily VA losses in 200 days. By conducting the Wilcoxon signed-rank tests, we find that the loss of the actual scenario is significantly smaller than ones of the three other scenarios. However, the difference of the total VA losses between Actual and Damage at once is small. The p values are smaller than 10^{-16}. The interpretation of the results are as follows.

Since Firm shuffle randomly picks up firms from the entire dataset, it can be said that this scenario is a so-called null model for the actual event. The average loss of Firm shuffle is significantly larger than one of the actual scenario. This result means that areas subject to the heavy rain are economically not pivotal or large. On the other hand, economically important areas are protected from disaster or those areas do not locate the vulnerable regions with consideration for the risks.

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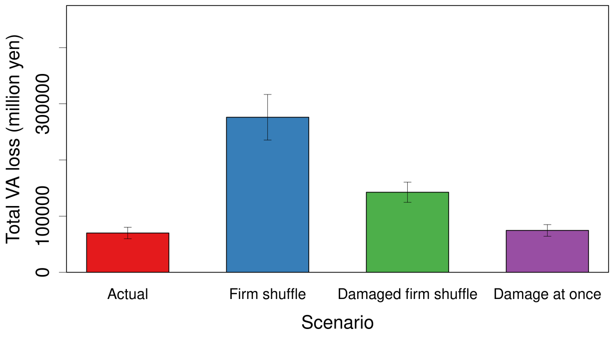

Figure 3: Total value-added loss. The average and standard error is indicated for each scenario. Each scenario has 100 Monte Carlo runs' results.

Table 1: Total value-added loss. The values for Figure3.

Scenario	Total VA loss in 200 days (million yen) Average	Standard error
Actual	74,584	10,372
Firm shuffle	287,516	40,751
Damaged firm shuffle	148,745	18,133
Damage at once	74,616	10,374

Next, Damaged firm shuffle is the scenario where firms in the actual scenario are randomly shuffled. All firms in the actual scenario are damaged by the heavy rain, but the intensity of the damage is different. Through this virtual scenario, we can examine whether or not firms subject to the heavy rains are the less important in the economy. As a result, the loss of Damaged firm shuffle is significantly larger than the actual scenario. Therefore, the above hypothesis is correct.

Finally, Damage at once is the scenario where firms in the actual scenario have the damage on the first day at the same time. The result shows that Damage at once is slightly but significantly larger than the actual scenario. Therefore, if the interval of the rain is short, it causes additional economic damage.

Since there are bilateral factors to aggravate and mitigate the loss by Damage at once, this result is interesting. One of aggravating factors is substitutability. In reality, if a firm cannot procure enough supply, it finds alternative suppliers. In the model, since a supply-chain network is fixed, a firm does not obtain new trade partners. Instead, if a supplier, which is already connected to the focal firm, has a surplus capability to supply to the focal firm, the supplier provide the supply to the focal firm. This is a part of substitutability of the actual supply chains, which also happens in reality. If the shock is simultaneous, i.e, Damage at once, there is more possibility for such alternative suppliers to be damaged directly or indirectly because of the simultaneousness of the shock.

Another aggravating factor of Damage at once, is a damping factor indicated in the model. The recovery of the damaged firm is damped if trade partners of the focal firm is also damaged. This effect is introduced into the model because of the empirical literature [1]. Obviously, this effect can aggravate the loss of Damage at once because the directly damaged firms have more possibility to be surrounded by the directly damaged firms in Damage at once.

On the other hand, cancelling effects occur in Damage at once and the total VA loss of Damage at once is suppressed by it. The cancelling effect is shown in literature [5]. The literature examines simulataneousness in the lockdown to prevent the COVID-19 spread and indicates that the simultaneous scenario indicates a less damage than the independent scenario and the interpretation for the result is cancelling effects. If areas of A and B are under lockdowns, a supply reduction from a firm in A to a firm in B may meet a demand reduction from the firm in B to the firm in A because all demand and supply of firms in A and B are reduced. However, in the heavy rain case, the areas are limited and besides, not all firms in the areas are affected unlike lockdowns. Therefore, there are scarce direct connections between damaged areas and bilateral demand and supply reductions. Therefore, it seems that the cancelling effects by direct conections are small.

As a summary for Damage at once, the scenario can examine the effect of the simultaneousness of the negative shocks. Although two aggravating and one mitigating factors, the result shows that the simulataneousness can aggravate the economic loss.

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