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Propagation of Negative Shocks through Firm Networks: Evidence from simulation on comprehensive supply chain data*

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Abstract

This paper examines how negative shocks due to, for example, natural disasters, propagate through supply chains, applying a simulation technique to actual data on supply chains of Japanese firms. We obtained the following five results. (1) Network structures severely affect the speed of propagation in the medium run and total loss in the long run. The scale-free nature of the actual supply chain network, i.e., the power law degree distribution, leads to faster propagation, while dense links between firms within the community in the actual network slow propagation. (2) More intensive damages, i.e., larger damages to fewer firms, result in faster propagation than extensive damages of the same total size. (3) When substitution of undamaged suppliers for damaged suppliers is more difficult to achieve, propagation of negative shocks becomes substantially fast. (4) Direct damages in industrial regions promote faster propagation than those in rural regions. (5) Different sectoral damages cause large differences in the speed of propagation and the long-run loss. All of these results imply that the same size of direct damages by disasters can generate considerably different damages, depending on the structure of the supply chain network in the economy.

Keywords: Supply chain, Propagation, Disaster, Simulation
JEL classification: L14

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1. Introduction

Natural disasters trigger economic damages directly as well as indirectly, as negative shocks of disasters are largely propagated through supply chain disruptions [Sheffi and Rice, 2005]. Such indirect damages are far from negligible and often constitute a large share of total damages [Tierney, 1997, Pelling et al., 2002]. For example, after the Great East Japan earthquake in 2011, a large number of firms unaffected by the earthquake directly including those in foreign countries had to stop operation due to shortage of supplies. Therefore, how and to what extent negative shocks propagate in the economy through supply chains has been quantitatively examined, using different economic models [Rose, 2004].

One major approach is based on input-output (IO) tables [Leontief, 1936], matrices of input-output relations among different sectors in the economy. More precisely, IO tables show how much inputs from each sector are required to produce one dollar of production in a sector. IO tables have been used to estimate effects of a shock in a sector on production in other sectors through inter-sectoral production relations [Haimes and Jiang, 2001, Santos and Haimes, 2004]. [Okuyama et al., 2004] particularly examine indirect effects of natural disasters by supply chain disruptions, using IO tables. Although earlier works rely on fixed IO tables before and after disasters, [Rose and Liao, 2005] incorporate flexible coefficients in IO tables by employing computable general equilibrium (CGE) models. In their model, the amount of inputs required for production in a particular sector is endogenously determined in the model and thus can be changed after a shock.

However, this approach using IO tables is clearly insufficient to examine propagation of negative shocks through supply chains, because IO tables capture production relations at the sector level, not at the firm level [Haimes and Jiang, 2001]. In other words, although how indirect damages propagate through supply chains heavily depends on how directly damaged firms are connected with other firms [Hallegatte, 2008], such networks at the firm level are not captured by IO tables.

To overcome this shortcoming of models based on IO tables at the sector level, [Henriet and Hallegatte, 2008] and [Henriet et al., 2012] propose an agent-based model where firms, rather than sectors, interact with each other through supply chains. Using the model, they simulate how damages by a negative shock propagate through supply chains. However, because they lack actual data on supply chain relations among firms, they rely on hypothetical random networks, although they incorporate actual IO relations at the sectoral level into the model. On the other hand, [Bak et al., 1993, Delli et al., 2005] utilized firm-level models but did not incorporate actual data.

The use of hypothetical networks, rather than actual ones, in simulation analysis is clearly a drawback, because the literature in network science has shown that a small difference in the network structure can lead to a substantial difference in behaviors of agents in the network [Newman, 2010, Barabási, 2016]. Recently, the literature in economics has also found the role of the structure of firm networks in propagation of negative shocks [Gabaix, 2011, Acemoglu et al., 2012]. Therefore, one may not obtain any reasonable conclusion about how damages in terms of production by natural disasters propagate through supply chains without using actual data of networks of firms in the economy. Such investigation has not been done, although propagation of negative shocks through financial networks of firms has been modeled [Gieseckey and Weber, 2006, Battiston et al., 2007] and empirically examined using actual data [Fujiwara and Aoyama, 2010, De Masi et al., 2011].

To fill the research gap, we apply comprehensive data on the nation-wide supply-chain network in Japan to a modified model of [Henriet and Hallegatte, 2008] and [Henriet et al., 2012] to tackle this issue. By simulating the model using different assumptions, we can address the following five important issues. (1) By comparing outcomes from actual networks and hypothetical ones used in the existing literature, we highlight the importance of the network structure in considering propagation of shocks though supply chains. (2) We examine how different intensity of direct damages leads to different indirect damages through supply chains, finding intensive damages, i.e., larger damages on fewer firms, result in faster propagation than extensive damages, smaller damages on more firms, of the same total amount of initial direct damages. (3) To highlight the importance of substitution of suppliers in the wake of supply chain disruption, we compare the benchmark case with cases where substitution is more restricted, finding a large role of substitution in mitigating propagation. (4) We examine how direct damages in different regions affect propagation pattern. This analysis reveals that direct damages in industrial areas result in faster propagation than those in remote areas, although the total amount of damages in the long run is the same. (5) Effects of direct damages in different sectors are also explored. Direct damages in sectors for which supply chains are more clustered in the region, most notably the construction sector, lead to a small indirect damages. All of these results suggest that propagation of negative shocks and total damages due to disasters largely depend on the structure of the supply chain network of the economy.

The remainder of this paper is organized as follows. Section 2 introduces the actual data. Section 3 describes the model used in our simulation analysis. Section 4 shows simulation results and discussion. Section 5 concludes the paper.

2. Data

We use two databases collected in 2011 by Tokyo Shoko Research (TSR), one of the two major corporate research companies in Japan, the TSR Company Information Database and the TSR Company Linkage Database. The databases are licensed to the Research Institute of Economy, Trade and Industry (RIETI). The TSR data contain a wide range of firm information, including identification numbers of suppliers and clients of each firm. Although the maximum number of suppliers and clients reported by each firm is 24, we can capture more than 24 suppliers and clients by looking at supplier-client relations from the opposite direction. That is, although a big firm, e.g., Toyota, reports only 24 suppliers, its suppliers are most likely to report the big firm as their clients. Accordingly, we identify the supply chain network of firms in Japan to a great extent. The number of firms, or nodes, is 1,109,549, whereas the number of supplier-client ties, or links, is 5,106,081. This network is directed, as it represents flows of intermediate and final products.

Firms are classified into sectors or industries. In the TSR data, industries are categorized by the Japan Standard Industrial Classification (JSIC) [Ministry of Internal Affairs and Communications, 2013]. The 1,460 classifications at the four-digit level of JSIC are converted into the 190 basic sector classifications of the IO tables, as we will later incorporate IO tables into the firm-level data.

Although the TSR data contain information about suppliers and clients, they do not include information on the value of transactions in each supplier-client tie. We conduct the following two-step calculations to estimate the transaction value. First, each supplier's sales are divided into its clients' purchases, using sales of the clients as weights. This step provides each link a transaction value. Although the transaction values at the tie level from the first step can be aggregated into transaction values at the sector level, i.e., from each sector to another, the sector-level transaction values from the firm level may not match those from IO tables. This inconsistency between micro and macro data is because the TSR data may not cover all firms in the economy. In addition, the TSR data do not capture transaction ties with final consumers. Therefore, in the second step, we modify the transaction values at the tie level by utilizing the IO tables for Japan in 2011 taken from [Ministry of Economy and Industry, 2011]. More specifically, the value of products of sector A sold to sector B that is taken from the IO tables is proportionally divided among all ties between suppliers in sector A and clients in B captured in the TSR data, using their tie-level transaction values as weights. Similarly, the value of final consumption of products of sector A in the IO tables is proportionally divided among all suppliers in sector A in the TSR data using their sales as weights. Through these steps, the aggregate of the tie-level transaction values equals those from the IO tables, and thus the value of damages estimated from our simulation can be reasonably compared with macroeconomic statistics, such as GDP.

3. Theoretical Model

We utilize the theoretical model proposed by [Henriet and Hallegatte, 2008] and [Henriet et al., 2012] with some modifications. This is an agent-based model where agents, i.e., firms and final consumers, follow specified rules. In the model, each firm in a sector produces a sector-specific product using a variety of intermediates and sells the product to its clients and final consumers. Further, we assume firms have inventories of intermediates to deal with possible supply shortage. An overview of the model is given in Figure 1, showing flows of products to and from firm i in sector r in particular.

We will later consider the situation where a natural disaster hits some firms in the economy so that production of some products does not necessarily meet demand due to direct damages and shortage of supplies. However, let us first describe the pre-disaster situation. The daily trade volume from supplier j to client i before the disaster is denoted by $A_{i,j}$, whereas the daily trade volume from firm i to final consumers is denoted as C_i. Then, the initial production of firm i in a day before the disaster is given by

$$P_{\text{ini}i} = \sum_j A_{j,i} + C_i. \tag{1}$$

We further assume that firm i has an inventory $S_{i,j}$ of the intermediate good produced by firm j and restores the inventory to a level equal to a given number of days $n_{i,j}$ of utilization of product j. On day t, the orders from firm i to its supplier j, denoted as $O_{i,j}(t)$, is then given by

$$O_{i,j}(t) = A_{i,j}\frac{D_i^*(t-1)}{P_{\text{ini}i}} + \frac{1}{\tau}\left(n_{i,j}A_{i,j}\frac{D_i^*(t-1)}{P_{\text{ini}i}} - S_{i,j}(t)\right), \tag{2}$$

where $D_i^*(t-1)$ is a realized demand for firm i on day t-1, the previous day, and τ is the number of days to adjust their inventory size. For example, when τ is six as we assume later in our simulations, firms plan to fill the gap between the projected inventory (i.e., $n_{i,j}$ days of demand) and the actual inventory gradually in six days. The first term of the right-hand side of equation (2) is the amount of product j that is needed to satisfy the demand on the previous day. The second term indicates the amount of product j that is needed to restore the inventory toward the projected level. Accordingly, the total demand for product i on day t, $D_i(t)$, is given by the sum of the final demand from consumers and the total orders from its clients:

$$D_i(t) = C_i + \sum_j O_{j,i}(t). \tag{3}$$

Now, suppose a disaster hits the economy and damages firm i directly. We assume that a certain proportion, δ_i, of production capital of firm i is destroyed by the disaster. Then, the production capacity of firm i, $P_{\text{cap}i}$, or its maximum production assuming no supply shortage is given by

$$P_{\text{cap}i} = P_{\text{ini}i}(1-\delta_i). \tag{4}$$

Production of firms may also be limited by shortage of supplies. Because we assume that firms in the same sector produce the same product, shortage of supplies from firm j in sector s can be compensated by supplies from firm k in the same sector if firm i has already transacted with j and k before the disaster (Figure 1). In other words, we do not assume changes in supply chain ties after the disaster. Then, total inventories of product s in firm i on day t is

$$S_{\text{tot}j,s}(t) = \sum_{j\in s} S_{i,j}(t). \tag{5}$$

Initial consumption of product s at firm i is also defined for convenience.

$$A_{\text{tot}i,s} = \sum_{j\in s} A_{i,j}. \tag{6}$$

Using the above two variables, $P_{\text{pro}i,s}(t)$, maximum production for firm i limited by inventory of product s on day t is obtained as follows.

$$P_{\text{pro}i,s}(t) = \frac{S_{\text{tot}j,s}(t)}{A_{\text{tot}i,s}} P_{\text{ini}i}. \tag{7}$$

Now, we can determine the maximum production of firm i on day t, considering its production capacity, $P_{\mathrm{cap}i}$, and its production constraints due to shortage of supplier, $P_{\mathrm{pro}i,s}(t)$:

$$P_{\mathrm{max}i}(t) = \mathrm{Min}\left(P_{\mathrm{cap}i}, \mathrm{Min}_s\left(P_{\mathrm{pro}i,s}(t)\right)\right). \tag{8}$$

Actual production of firm i on day t is, therefore, given by

$$P_{\mathrm{act}i}(t) = \mathrm{Min}\big(P_{\mathrm{max}i}(t), D_i(t)\big). \tag{9}$$

When the demand for a firm is greater than its production capacity, the firm cannot completely satisfy its demand, as is denoted by equation (9). In this case, firms should ration their production to their clients. [Henriet and Hallegatte, 2008] proposed a rationing policy where each of all client firms and final consumers receives the amount of products that is the same fraction ($P_{\mathrm{act}i}/P_{\mathrm{ini}}$) of its pre-disaster trade volume. However, this may not be the case in practice. For example, suppose that client h of firm i in sector r increases its demand for product r after the disaster because other suppliers of product r for client h are destroyed. Then, according to this rationing policy, firm i will decrease supply of product r to other firms although they are not affected directly by the disaster or indirectly by their suppliers. Thus, this rationing policy is most likely to augment propagation of negative shocks, leading to overvaluation of effects of disasters. For example, 10% damages ($\delta = 0.1$) for firms can result in complete incapability of a supply chain network, which may not happen in the actual economy.

Therefore, we employ another rationing policy, in which firms are prioritized according to the level of order after the disaster to their initial order. (Note that we do not have to consider a rationing policy if the production capacity is larger than demand.) To explain this policy more specifically, let's suppose that firm i producing r has two client firms, g and h, and a final consumer (See Figure 1). Because of disasters, demand of clients g and h decreases, and importantly, product r of firm i cannot fill the demand. For example, assume that the ratio of post-disaster orders to pre-disaster orders (hereafter, the post-to-pre order ratio) is 0.1 and 0.2 for firm g and h, respectively. By contrast, the corresponding ratio for final consumers remains one. As a first step, firm i calculate the tentative demand by applying the minimum post-to-pre order ratio (0.1 for client g) to all clients and the final consumer. If the tentative demand is larger than the firm i's production capacity (precisely, this is remaining capacity as is explained later.), firm i apply the same post-to-pre order ratio for all clients and the final consumer so that the total demand is equal to the production capacity. Accordingly, the rationing process is completed. On the other hand, if the tentative demand is smaller than the firm i's production capacity, firm i first provides each client its pre-disaster order times the minimum post-to-pre order ratio among clients. Now, although the demand from the client with the minimum post-to-pre order ratio is fully met, the demand from other clients remain. Then, we will follow the same procedure from the beginning until the production is completely provided to clients and final consumers.

Following this rationing policy, Then, the realized total demand for firm i, $D_i^*(t)$, is given by

$$D_i^*(t) = C_i^* + \sum\nolimits_j O_{i,j}^*(t)_{j,i}, \tag{10}$$

where the realized order from firm i to supplier j is denoted as $O_{i,j}^*(t)$, and the realized demand from final consumers is C_i^*. Accordingly, the inventory of firm j's product in firm i is modified to

$$S_{j,i}(t+1) = S_{j,i}(t) + O_{j,i}^*(t) - A_{j,i}\frac{P_{\mathrm{act}j}(t-1)}{P_{\mathrm{ini}j}}. \tag{11}$$

Using the model above, we simulate how direct damages by a natural disaster, represented by exogenous reduction in production capacity of a set of firms, affect the production of the whole economy through propagation of negative shocks along supply chains. In the simulation, we utilize the actual supply chains of firms in Japan, taken from the TSR data. $A_{j,i}$ and C_i are determined from the IO tables and supply chain ties as described in Section 2. We assume that τ is six whereas $n_{i,j}$ is 15. That is, firms aim to have inventories of supplies for 15 days, and when inventories are insufficient, they try to fill the gap gradually in six days.

In each simulation, exogenous damages are given on day 0. Specifically, our benchmark simulation assumes that 10,000 firms randomly selected from the total of 1,109,549 lose 50 percent of their production capacity after the disaster (i.e., δ in equation (4) is 0.5), although we experiment with other types of shock as we will explain later. In other words, the benchmark cases assume that approximately 0.5 percent (10,000 * 0.5/1,109,549) of the total production capacity in the economy is destroyed. Then, we examine how the sum of value added, or the value of production less the total value of intermediates used for the production, of all firms in the economy changes over time. For each set of parameter values, we simulate 30 times and show the results graphically, using a solid line for the average value added and dotted lines for its standard deviations.

Because the simulation in this study requires substantial computational power due to more than one million agents and five million ties, we utilize a supercomputer and run simulations in parallel to minimize the run time. Since the simulation can be executed independently for each trial, it can be categorized into so-called embarassingly parallel simulation and the parallel execution reduces the consumption of wall time without loss. The simulation code is shared on GitHub so that the reader can run their own agents and networks. The code provides abundant variations of simulations. See the detail on the web site.[2]

4. Simulation Results and Discussion

4.1 Benchmark result

Our benchmark result using the actual supply chain network and the parameter values explained above is shown by the red line in Figure 2. The simulation result indicates that value added declines from 420 trillion yen before the disaster to 370 trillion 30 days after the disaster and further to 220 trillion 100 days after the disaster and is stable after that. Thus, although the direct damage was only 0.5 percent of value added, the total damages including indirect damages by supply chain shortages reach approximately 12 percent of value added in 30 days and 48 percent in 100 days. Therefore, we

2 https://github.com/HiroyasuInoue/ProductionNetworkSimulator

conclude that indirect effects of disasters through supply chain disruptions can be enormous.

One may think why we observe the wavy trajectory for each simulation. The waves come from the inventory size we assume in the simulation and it is set to 15 days for all firms. Therefore, 50% reduction of supply rased by shock deplete clients inventory 30 days later at once. This is the reason why we observe the first wave around 30 days and other successive waves.

In our simulation, value added converges to a certain value in the long run because a steady state is achieved when negative shocks reach all firms indirectly connected to directly damaged firms through supply chains. In addition, because we do not assume any recovery, or restoring production capacity by repair and replacement of capital goods, value added monotonically declines over time and converges to a lower level than the pre-disaster level. This assumption of no recovery is obviously too strong in practice. In the case of the Great East Japan earthquake in March 2011, firms at the impacted areas stopped operation for only five days at the median [Todo, et al., 2015]. Renesas Electronics, a major producer of microcomputers for automobiles that was heavily hit by the earthquake, recovered in June, 2011, taking three months for recovery. Accordingly, although some factories for final assemblies of automobiles which were not directly hit had to stop operation for a few months due to supply chain disruptions, production of automobiles recovered to the pre-earthquake level in July, 2011.

Therefore, the long-run consequences from our simulations may not signify actual damages from disasters, by ignoring recovery processes. [Todo, et al., 2015] show that recovery from the Great East Japan earthquake was indeed promoted by supply chain partners because supporting partners' recovery was beneficial to firms in the network. Our current model ignores this aspect, overestimating the long-run effect of disasters through supply chains. Therefore, when we interpret the simulation results, we focus more on the change in value added in the medium run, i.e., within 100 days, although we may be interested in the total loss in value added in the long run (one year) in some particular contexts.

4.2 Differences between the actual network and random networks

Now, we show differences in propagation of negative shocks between the actual network and randomly generated networks. Although [Henriet and Hallegatte, 2008] and [Henriet et al., 2012] used a type of random networks in their simulation, the advantage of the use of the actual supply chain network is clear. The distribution of the degree (the number of links) in the actual supply chain network in Japan is fat-tailed and follows the power law, as found in [Fujiwara and Aoyama, 2010, Inoue, 2016]. It has been repeatedly discussed that networks with a power-law distribution, or scale-free networks, show unique properties in many respects [Barabási, 2016]. In the context of this study, propagation in the actual network is found completely different from that in networks with other structure, such as complete graphs, or random networks. Therefore, to examine how negative shocks by natural disasters propagate through supply chains in practice should be empirically examined using the actual network of supply chains, rather than random networks.

To check differences between the actual and random networks, we experiment with two types of random networks. First, we randomly generate networks with the same number of nodes and links as the actual (1,109,549 nodes and 5,106,081 links), using the algorithm developed by [Gilbert, 1959] where we set p at approximately 8.30×10^{-6}. Second, we restrict random networks further so that the degree of each node is the same as the actual network while the pair of nodes conneced by the link is randomized, using the algorithm of [Maslov and Sneppen, 2002]. As we mentioned above, a large difference between the actual network and random networks is the power-law distribution of the degree in the former. By comparing results from the actual network and degree-preserving random networks, we can highlight differences stemming from other characteristics of networks, such as density. In each case, we generate 30 different random networks and show the average and standard deviation of the change in value added graphically.

In Figure 2, the red, blue, and green lines respectively indicate the results using the actual network, degree-preserving random networks, and random networks where further the degree distribution is the same. The comparison between the results from the actual network and the less-restricted random networks, i.e., the red and blue lines, clearly shows that damages due to direct and indirect effects of the disaster in the medium and long run are substantially larger in the actual network than in random networks. The simulation results show that damages from disasters are likely to be underestimated if supply chains are assumed to be random and that we should use actual scale-free networks in simulation.

The difference can be explained by differences in path lengths in the network. A path length is the number of steps between arbitrary two nodes in a network, and the average path length is the average of all possible path length. The average path length of a random network, $\langle d \rangle$, is proportional to the natural logarithm of the number of nodes, N, or $\langle d \rangle \sim \ln N$. To the contrary, a scale-free network, which is the case with the supply chain network in Japan [Fujiwara and Aoyama, 2010], has different properties from random networks [Barabási and Albert, 1999]. In particular, it is found that the average path length is proportional to the log of the log of the number of nodes: $\langle d \rangle \sim \ln \ln N$. That is, the actual supply chain network has a much shorter average path length than random networks, suggesting that shocks spread faster in the actual network than in random networks.

In addition, indirect damages in random networks is less amplified by the rationing policy assumed in our model and described in Section 3.2. The rationing policy assumes that demand from producers affected by the disaster is prioritized to demand from final consumers. Reduction of provision to final consumption can work as absorption of supply-driven damages. When path lengths are longer, shocks can be absorbed more. Therefore, damages in the actual network with a shorter average path length are substantially greater than those in random networks with a longer length.

However, when we compare results using the actual network (the red line) and degree-preserving random networks (the green line) in Figure 2, we find that degree-preserving random networks lead to faster propagation of damages than the actual network in the short term (within a month), although resulting in a similar total loss in the long run. The difference in the short term can be explained by its density or community structure. In the actual network, some firms are densely connected, that is, firms' partners are also connected with each other, forming communities of firms. Communities are more likely to be formed within regions, sectors, or keiretsu relations. As a result, 11.5 percent of nodes in the actual network have two-step (reciprocal supply relations) circuits, while the corresponding figures are 0.7 percent in the degree-preserving random networks. Therefore, in the actual network, propagation of damages across communities takes more time than within such strucutures, and thus value added declines more slowly than in the others. However, in the long run, because damages propagate to all firms, the total loss in value added is similar in the two cases.

Our results clearly show that network structures of supply chains play an important role when we simulate indirect damages from disasters through supply chains. In particular, the comparison between the actual network and random networks with the same number of nodes and links indicates the importance of the scale-free degree distribution in faster propagation, whereas the comparison between the actual and degree-preserving random networks signifies the importance of network density in slower propagation.

4.3 Different intensity of damages

Next, we experiment with different intensity of damages, assuming three cases: 50,000 firms lose 10 percent of their production capacity; 10,000 lose 50 percent, as in the benchmark case; and 5,000 lose 100 percent. Note that the total capacity loss in the economy, approximately 0.5 percent for 10,000 firms, is the same across the three cases. Damaged firms are randomly selected in each case.

The results from the simulation are shown in Figure 3. The comparison between the three shows that more intensive damages, i.e., larger damages on fewer firms, result in faster propagation of damages and larger total loss in value added. In particular, when production capacity of even a small set of firms is completely lost in the third case, 80 percent of value added will be lost in the long run. This is because clients of destroyed suppliers may not produce their products, negative effects can quickly propagate through supply chains. Our results are consistent with [Henriet and Hallegatte, 2008] and [Henriet and Hallegatte, 2008] who used random networks in their simulation.

4.4 Substitution among suppliers

Another important issue is substitution of suppliers for mitigation of damages. As shown in Section 3, our model assumes that when supplier *j* of product *s* to firm *i* is damaged by a disaster, firm *i* can substitute supplies from firm *j* for those from firm *k* (Figure 1). When such substitution is more feasible, indirect damages through supply chains can be mitigated more.

To investigate this issue, we experiment with two alternative cases in which products (sectors) of suppliers are changed. In one case, products of firms are randomly determined while preserving the distribution of products as in the actual network. Then, because firms utilize a larger variety of intermediates, substitution is more difficult than in the actual economy. In another alternative case, the product of each firm is completely differentiated from products of other firms, so that substitution among suppliers is impossible.

Figure 4 shows the results using the benchmark case (the red line) and assuming random assignment of products (green) and completely differentiated products (blue). This figure indicates that in the latter two case where substitution among suppliers in the case of supply chain disruption is more difficult than in the actual case, propagation of negative shocks is substantially faster. Therefore, substitution of undamaged suppliers for damaged ones is shown to be an important channel of mitigation of shock propagation.

4.5 Region- and sector-specific damages

So far, we assumed that firms affected by the disaster are randomly selected across regions and sectors. However, natural disasters such as earthquakes and typhoons often affect specific regions. In addition, shocks in the economy may be caused not by natural disasters but by, for example, financial crises, technological progress, and deregulations. These human-made shocks are more likely to be sector specific. Therefore, we now examine propagation of region- and sector-specific shocks.

First, we assume that firms in a particular region are damaged. We divide Japan into eight regions, Hokkaido, Tohoku, Kanto, Chubu, Kinki, Chugoku, Shikoku, and Kyusyu. As in the benchmark simulation in Section 4.1, we assume that 10,000 firms randomly chosen from each region lose 50 percent of their production capacity. Results in Figure 5 show that damages in Kanto and Kinki propagate most rapidly, although the total loss in the long run is the same across regional damages. Kanto includes the largest metropolitan area in Japan, Tokyo and Yokohama, whereas Kinki includes the second, or Osaka. Therefore, our results indicate that damages propagate faster when industrial areas are hit than when remote areas are. The difference at the first wave of the degradation is substantial, because 30 days after the disaster, direct damages in the Tohoku region where the Great East Japan earthquake actually hit in 2011 result in a loss in value added of 25 trillion yen, or 5 percent, while the loss from damages on the Kanto region is 47 trillion yen, 11 percent. Therefore, it is expected that the Tokyo earthquake and the Nankai Trough earthquake that are predicted to hit Tokyo in the near future will cause substantially larger damages in the Japanese economy than the Great East Japan earthquake in 2011.

On the other hand, after the first wave of the degradation, there is no significant difference in long-run damages between regional shocks. This is because most firms in Japan are connected within small steps through supply chains. To understand this, Figure 6 illustrates damages in the first wave in two cases, one in which the Kanto region, the economic center of Japan that includes Tokyo, is directly hit, and the other in which the Tohoku region, a relatively less developed region, is hit. The top figure shows the geographical plots of damaged firms in the first wave of damage propagation due to direct damages in Kanto, whereas the bottom shows those due to direct damages in Tohoku. In both cases, as the first wave already reaches most regions of Japan, the second wave reaches a large proportion of firms in Japan so that total damages are not different from each other. This finding indicates that even if damages in the first wave of propagation are small, insufficient recovery from the first wave can result in serious damages propagating into the entire economy through supply chains.

Second, we assume that firms in a particular sector among the 190 are damaged. Because we need more than 10,000 firms in a sector to run the simulation, we focus on 15 sectors in which there are more than 10,000 firms in our data. The list of the 15 sectors as well as the simulation results is shown in Figure 7. The results indicate substantial variations in the medium run: Propagation is faster when some sectors such as pulp, paper, and wood, plastic and latex, miscellaneous manufacturing, are directly damaged, while it is slow when others such as real estate and medical, health care and welfare. Most notably, when the construction sector is hit, there is little propagation of negative shocks.

The results can be mainly interpreted by whether hub firms exist in the directly damaged sector. A scale-free network has a few hubs that have extremely many links. Therefore, if the sector includes such hubs, propagation is naturally fast. Unlike most manufacturing sectors, service sectors such as the construction, medical services, and real estate sectors are less likely to have hub firms in supply chains. This is probably one reason why damages in these sectors may not be as destructive as those in others.

5. Conclusion

We used nation-wide supply-chain network data of Japan and employed a modified version of the model of [Henriet and Hallegatte, 2008] to examine how negative shocks by disasters propagate through supply chains. We obtained the five results. (1) Network structures severely affect the speed of propagation in the short run and the total loss in the long run. The scale-free nature of the actual supply-chain network, i.e., the power-law degree distribution, leads to faster propagation, while dense links between firms within the community in the actual network slow propagation. (2) Different intensity of damages leads to different speed of propagation. More intensive damages, i.e., larger damages on fewer firms, result in faster propagation than extensive damages of the same total size. (3) Substitution among suppliers largely contributes to resilience of the economy. When substation becomes more difficult, propagation of negative shocks becomes substantially fast. (4) Direct damages in industrial regions promote faster propagation than those in rural regions, although the total loss in value added in the long run is the same. (5) Different sectoral damages cause large differences in the speed of propagation and the long-run loss. In particular, effects of direct damages on the construction sector are quite small. All of these results imply that the same size of direct damages by disasters can generate considerably different damages, depending on the structure of the supply-chain network in the economy.

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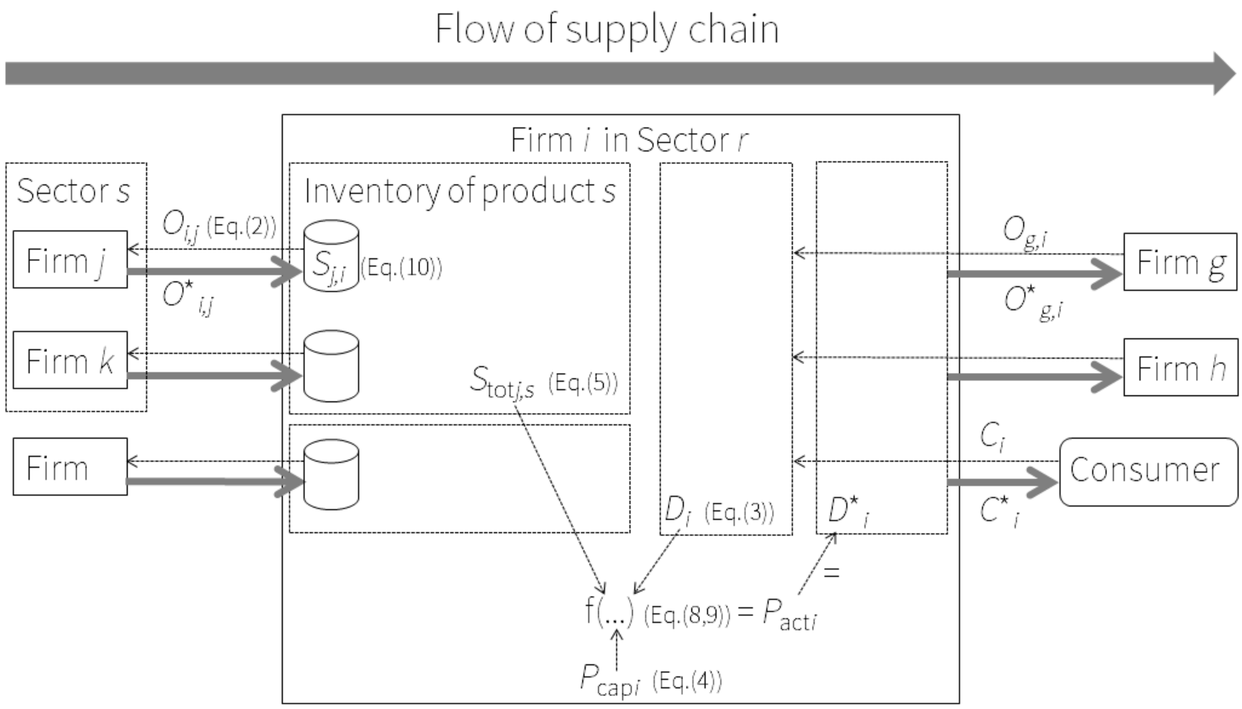


Figure 1: Overview of model. The flow of the product is from left to right but orders have the opposite direction. Most equations are embedded with the reference numbers. Inventories are bound for each product. Actual production is a function of product inventories, production capacity, and demand. The actual production is equal to the realized demand.

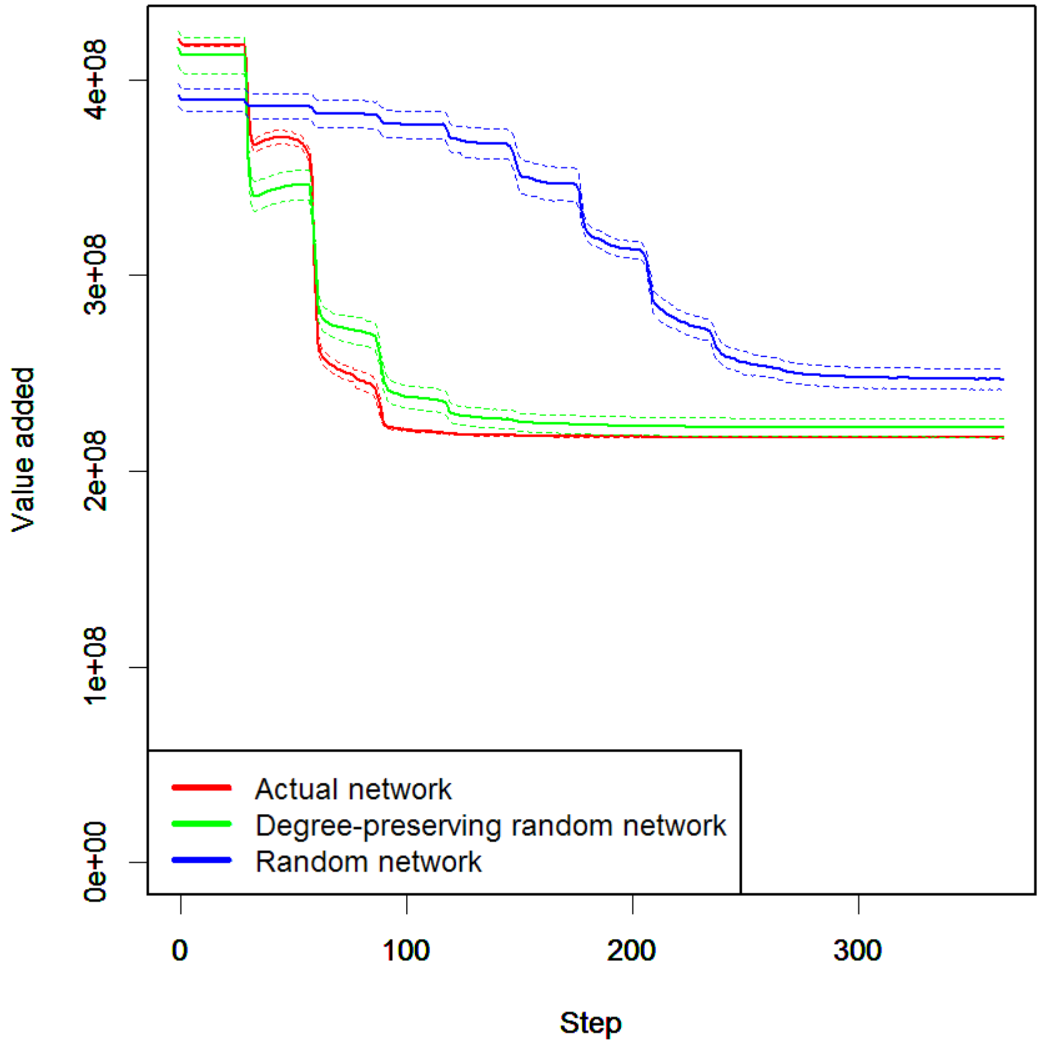


Figure 2: Simulation results using different network structures. The horizontal axis shows steps (days), whereas the vertical axis shows total value added of the system. The red, green, and blue lines respectively show the results for the actual network, degree distribution-preserving random networks, and random networks. The solid lines show the average of 30 simulations. The dotted lines show the standard deviations. In all simulations, it is assumed that randomly selected 10,000 firms lose 50 percent of production capacity at step 0 ($\delta = 0.5$).

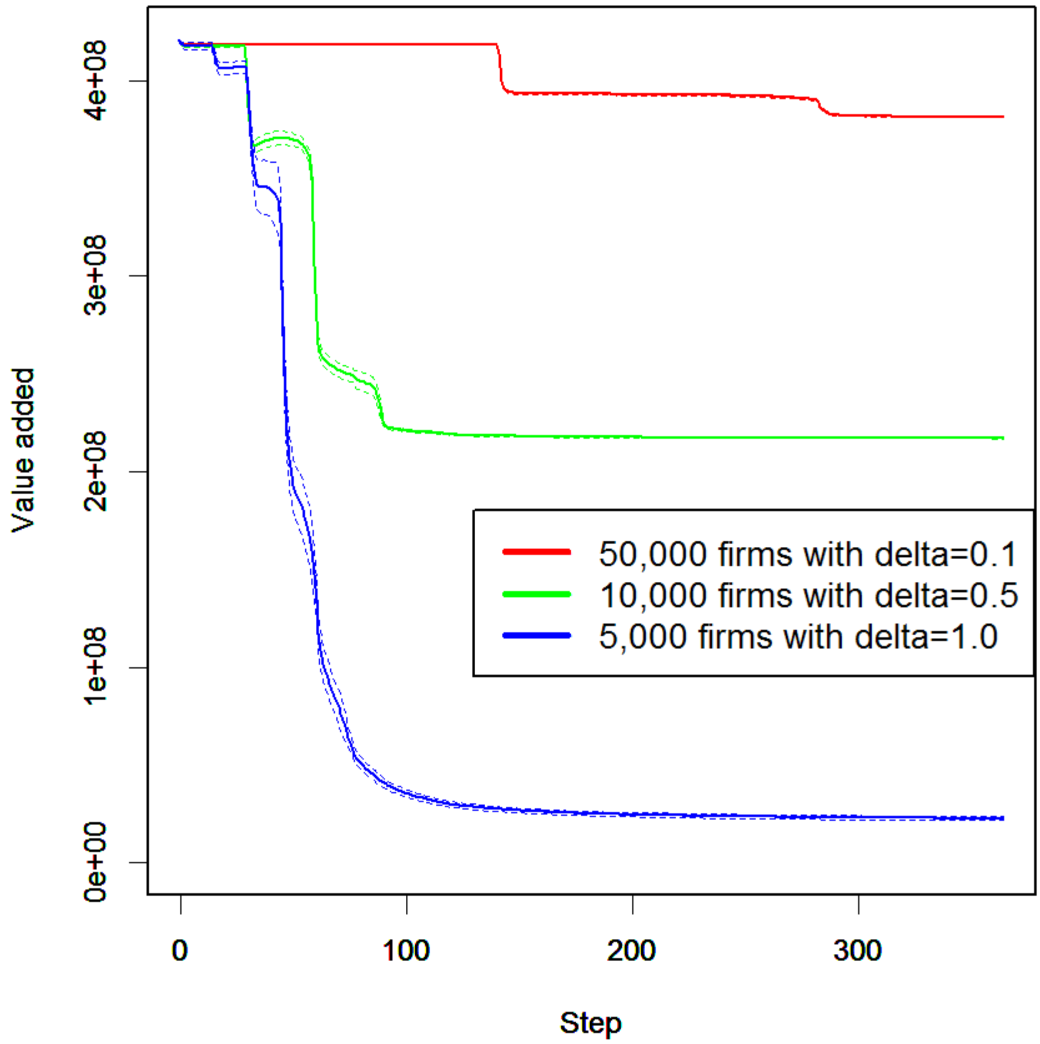


Figure 3: Simulation results using different intensity of shocks. The horizontal axis shows steps (days), whereas the vertical axis shows total value added of the system. The red, green, and blue lines respectively show the results assuming that 50,000 firms lose 10 percent of production capacity ($\delta = 0.1$), 10,000 lose 50 percent ($\delta = 0.5$), and 5,000 lose 100 percent ($\delta = 1$). The solid lines show the average of 30 simulations. The dotted lines show the standard deviations.

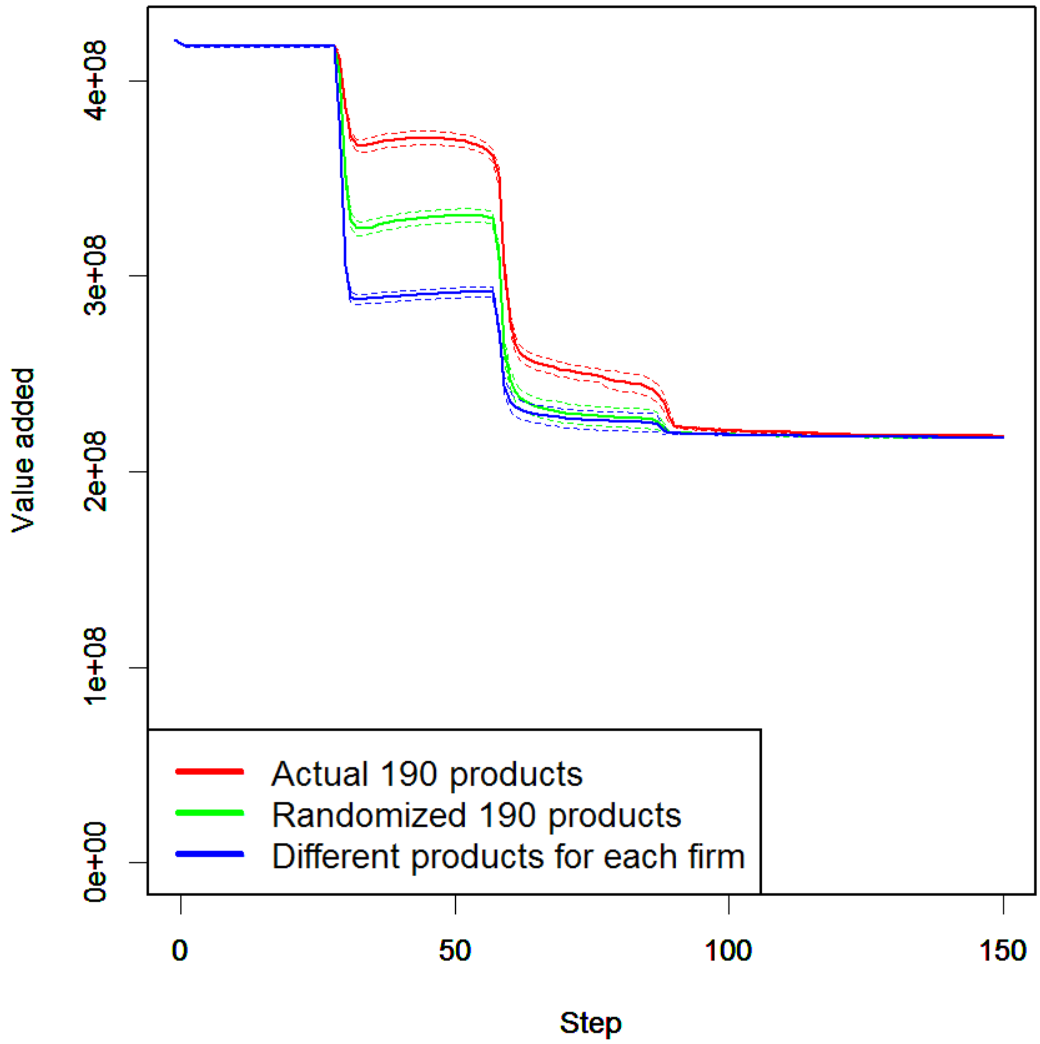


Figure 4: Simulation results assuming different features in substitution among suppliers. The horizontal axis shows steps (days), whereas the vertical axis shows total value added of the system. The red, green, and blue lines respectively show the results using the actual products of firms, randomizing products, and completely differentiating products. The solid lines show the average of 30 simulations. The dotted lines show the standard deviations. In all simulations, it is assumed that randomly selected 10,000 firms lose 50 percent of production capacity ($\delta = 0.5$).

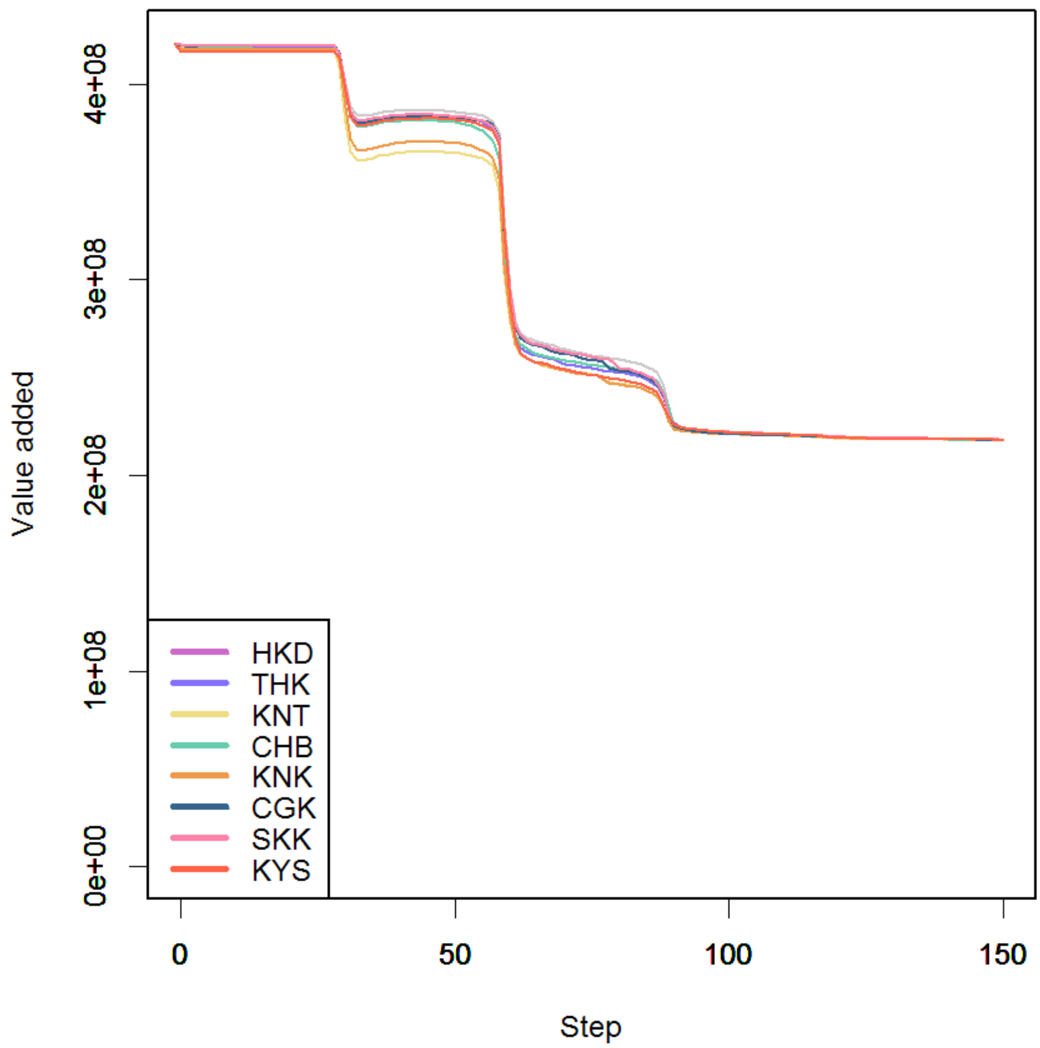
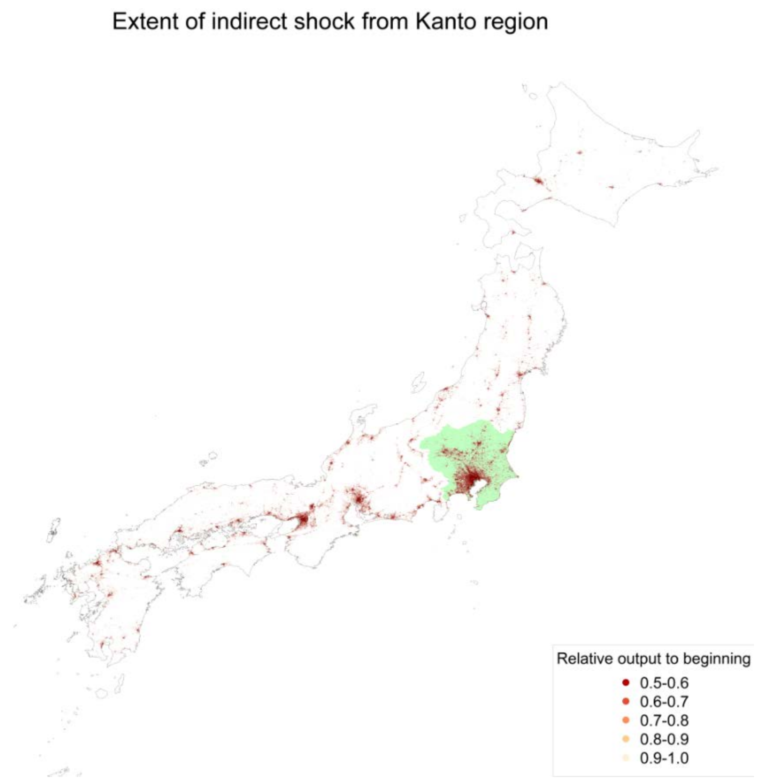


Figure 5: Simulation results using different regional shocks. The horizontal axis shows steps (days), whereas the vertical axis shows total value added of the system. The solid lines show the average of 30 simulations. It is assumed that 10,000 firms randomly chosen in each of the eight regions, Hokkaido (HKD), Tohoku (THK), Kanto (KNT), Chubu (CHB), Kinki (KNK), Chugoku (CGK), Shikoku (SKK), and Kyusyu (KYS), lose 50 percent of production capacity.



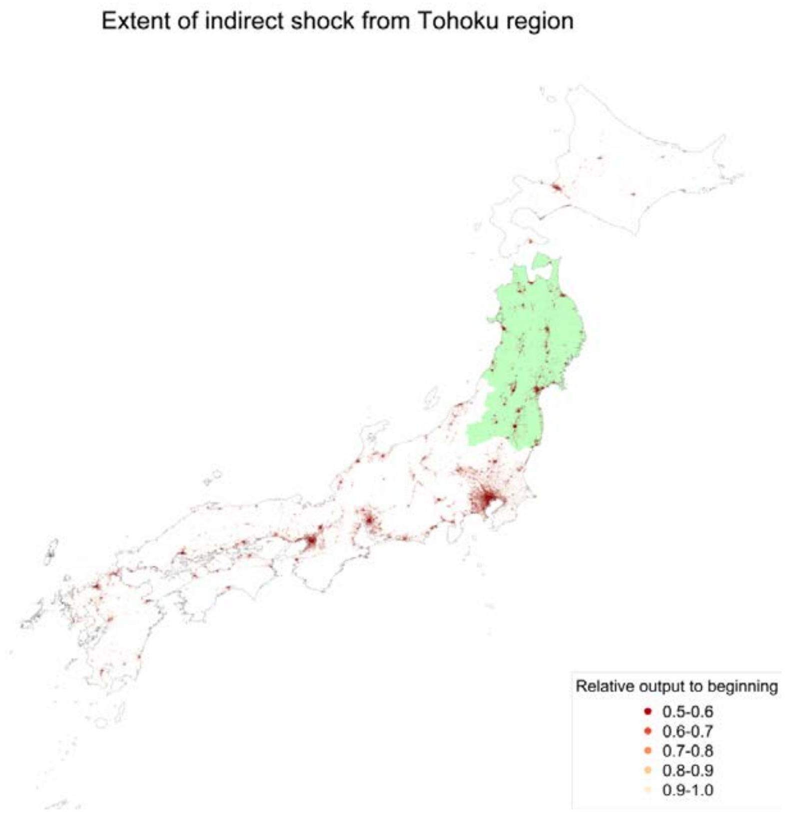


Figure 6: Geographical plots of regional shocks. The top figure shows a snapshot of relative outputs to the beginning at 30 day in Kanto region. Kanto region is coloured with light green. The bottom figure corresponds to the same figure for Tohoku region.

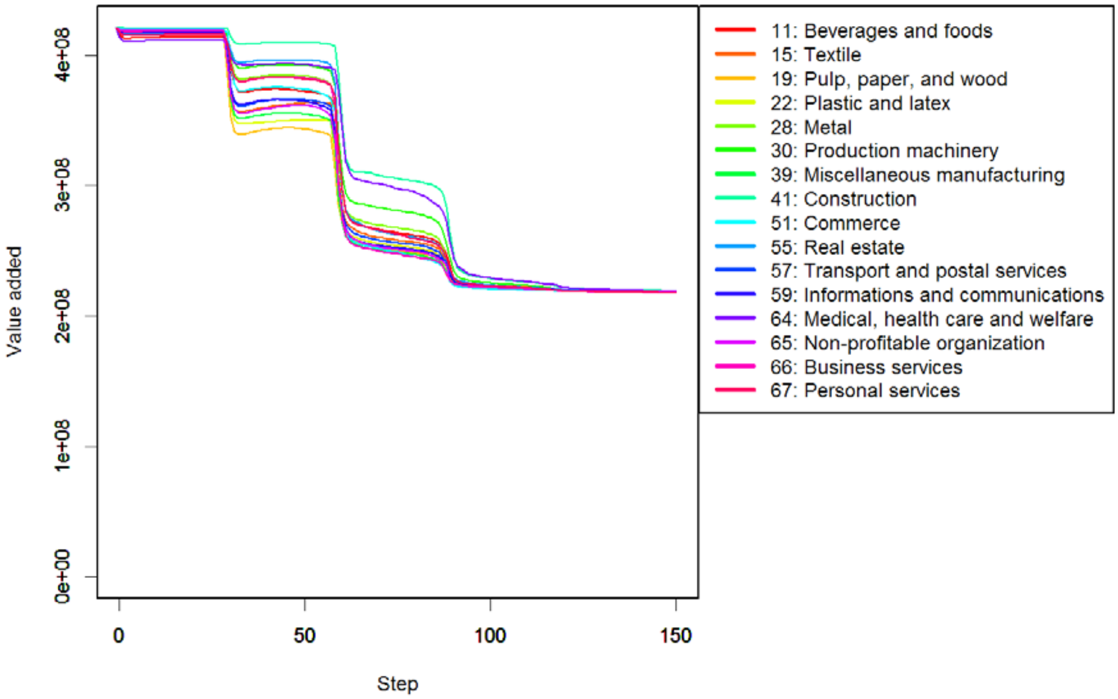


Figure 7: Simulation results using different sectoral shocks. The horizontal axis shows steps (days), whereas the vertical axis shows total value added of the system. The solid lines show the average of 30 simulations. It is assumed that 10,000 firms randomly chosen from each of 12 sectors lose 50 percent of production capacity.