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# Establishment-level simulation of supply chain disruption: The case of the Great East Japan earthquake*

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Abstract

This paper simulates the economic loss resulting from supply chain disruptions triggered by the Great East Japan Earthquake (GEJE) in 2011, applying data on firm-level supply chains and establishment-level attributes to an agent-based model. In particular, we improve previous studies on this issue in the following four ways by modifying the model and data and thus by estimating more accurate parameter values. First, our model incorporates more parameters, some of which vary across sectors, than the previous models. Second, our data can identify the damage to production facilities in the disaster-hit regions more accurately, using establishment-level census and survey data and geographic information system (GIS) data on the GEJE and subsequent tsunami. Third, the use of the establishment-level data enables us to capture supply chains between non-headquarter establishments in the disaster-hit regions and establishments in other regions, even though we cannot capture the whole network at the establishment level. Finally, we incorporate power outages after the GEJE that exacerbated the supply chain disruption, particularly for a few weeks immediately after the GEJE. We find that our extended method can greatly improve the capability of replicating the actual economic outcomes after the GEJE, and this improvement is mostly due to the last three improvements, and not because of the use of more parameters. Our method can be applied to predict the economic effect of future disasters, such as the Nankai Trough earthquake, on each region more accurately.

Keywords: supply chains, disaster, simulation, parameter calibration, parallel computing
JEL classification: L14



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# 1 Introduction

How the effect of an economic shock by, for example, a natural disaster, propagates through supply chains has been studied extensively (Hallegatte, 2019). Several studies employ an econometric approach using firm-level data and find that firms that are not directly affected by a disaster but linked with directly affected firms through supply chains tend to decrease their production (Barrot & Sauvagnat, 2016; Carvalho *et al.*, 2021; Boehm *et al.*, 2019; Kashiwagi *et al.*, 2021). Another strand of literature takes a simulation approach using supply-chain models and data. For example, Inoue & Todo (2019a,b) apply an agent-based model to the case of the Great East Japan earthquake (GEJE) in 2011 and estimate values of parameters in the model using detailed data on domestic supply chains of approximately one million firms in Japan and production of Japan after the GEJE. The model of Inoue & Todo (2019a,b) is further applied to predict the effect of lockdown of cities and regions to prevent the spread of COVID-19 in 2020-2021 on production (Inoue & Todo, 2020; Inoue *et al.*, 2020). Although other studies also estimated the economic effect of the GEJE and COVID-19 lockdown using similar models and data on industry-level input-output linkages (Tokui *et al.*, 2017; Guan *et al.*, 2020; McKibbin & Fernando, 2020), an advantage of Inoue & Todo (2019a,b) is that their analysis is based on firm-level supply chains. In other words, the simulation of Inoue & Todo (2019a,b) can incorporate behaviors arising from complexity of networks (Barabási, 2016) and thus is more likely to replicate the dynamics of the economic effect of the GEJE more accurately than other studies based on industry-level linkages.

This study extends the model, data, and calibration method used in Inoue & Todo (2019a,b) in four ways to provide a better fit between the actual and simulated production of Japanese firms after the GEJE. First, we employ more parameters by defining that some parameters vary across sectors. Second, this study use establishment-level census data, unlike the previous studies that rely on firm-level data, such as Inoue & Todo (2019a,b), as well as Barrot & Sauvagnat (2016), Carvalho *et al.* (2021), and Kashiwagi *et al.* (2021). In addition, we employ data from an establishment-level survey in the disaster regions after the GEJE and detailed geographic information system (GIS) data on the earthquake intensity and the tsunami height. The use of these various data sets enables us to identify damage to production facilities, particularly those of non-headquarter establishments whose headquarters were outside the disaster-hit regions, by the GEJE and the subsequent tsunami more accurately. Third, our supply chain data are at the firm level as in the previous studies. However, using establishment-level data, we can identify supply chains between non-headquarter establishments in the disaster regions and establishments in other regions through their headquarters. This modification helps us to estimate propagation of the GEJE shock from the disaster regions to others more accurately than in the previous studies. Finally, in addition to damage to production facilities by the GEJE examined in Inoue & Todo (2019a,b), we incorporate into our simulation power outage after the GEJE that was caused directly by the disaster and indirectly by the accident of the Fukushima Daiichi Power Plant and exacerbated the effect of supply chain disruption. Accordingly, this study can explain the large decline in production immediately after the GEJE that is not accurately predicted in the previous studies.

# 2 Data

This study utilizes several data sources. This section explains these sources and how we combine them together.

## 2.1 Supply-chain data at the firm level

The main source of our analysis is data of Japanese firms collected by Tokyo Shoko Research (TSR), particularly, the Company Information Database and Company Linkage Database. The former dataset contains attributes of each firm, including its address, industry classification, and sales, while the latter consists of its domestic clients and suppliers. We specifically use the data for 2011, the year of the GEJE. The number of firms in the dataset is 1,161,096, and the number of supply chain links is 5,361,130. The data cover most firms in Japan, except for micro enterprises, and most major supply chain relationships between them.

Because sales of each supplier from each client and final consumers are not available in the data, we estimate the transaction value between each firm pair using the value between each sector pair taken from the 2015 Input-Output (IO) Tables for Japan (Ministry of Internal Affairs and Communications, the Cabinet Office, the Financial Services Agency, the Ministry of Finance, the Ministry of Education, Culture, Sports, Science and Technology, the Ministry of Health, Labour and Welfare, the Ministry of Agriculture, Forestry and Fisheries, the Ministry of Economy, Trade and Industry, the Ministry of Land, Infrastructure, Transport and Tourism, and the Ministry of Environment, Japan, 2015). More precisely, sales of a firm to each of its clients are determined proportionally to the client's total sales, and its sales to final consumers are determined proportionally to the firm's total sales. The value of transaction between each firm pair and between each firm and final consumers is adjusted so that the sum of the inter-firm transaction values for each industry pair and firm-to-consumer transaction values for each industry is the same as in the IO Tables. In this estimation process, we classify firms into 187 industries according to the IO Tables, although in the simulation later, firms are classified into 1,460 industries according to the Japan Standard Industrial Classification (Ministry of Internal Affairs and Communications, 2013). Some firms are dropped from the sample because they lack total sales in the data. As a result, the number of firms in the sample is 966,627, whereas the number of links is 4,543,557.

## 2.2 Census data at the establishment level

Although the TSR data are quite useful in that they contain detailed supply-chain information of approximately one million firms, one shortcoming of the TSR data is that it does not include information of the location of establishments of each firm, except for its headquarter. Therefore, we utilize data from the Economic Census for Business Activity (hereafter the Census) that are collected by the Ministry of Internal Affairs and Communications and the Ministry of Economy, Trade and Industry (Ministry of Internal Affairs and Communications and Ministry of Economy, Trade and Industry, 2016) and target all establishments in all industries in Japan, including establishments of micro-, small-, and medium-sized enterprises. We use the Census data for 2016 where the number of establishments is 5,880,504[5]. We merge the Census data with the TSR data using firms' names, addresses, and telephone numbers. As a result of this merging process, we add 1,014,673 non-headquarter establishments to the TSR data. Hereafter, we denote this combined data as the TSR-Census data.

The Census data contain information on sales and the location of each establishment. Although the Census data do not include any information on supply chains at the establishment level, we can still identify supply chains between establishments if they are linked at the firm level. Therefore, using the TSR-Census data enables us to specify damage to establishments in the disaster regions and examine the propagation of its effect through supply chains between establishments more accurately.

[5]We also use the Economic Census for Business Activity in 2012 collected by the Ministry of Internal Affairs and Communications and the Ministry of Economy, Trade and Industry and the Economic Census for Business Frame in 2009 and 2014 collected by the Ministry of Internal Affairs and Communications to check the overall trend in the data and the validity of the use of the data for 2016.

## 2.3 Data on damage to production facilities and power outage

To identify the level of damage to production facilities at the establishment level, we additionally use data from an establishment-level survey conducted by the Research Institute of Economy, Trade and Industry one year after the GEJE titled "Questionnaire Survey on Damages to Companies Caused by the Great East Japan Earthquake" (hereafter the RIETI data) (Hamaguchi, 2012; Todo *et al.*, 2015). The targets are 6,033 establishments in the manufacturing sector in the publicly defined disaster-hit regions, except for those in the regions most severely affected by the tsunami because of the difficulty of the implementation of the survey. The number of respondents is 2,117, so that the response rate is 35%. The RIETI survey asked each respondent about the level of damage to its production facilities, using a scale of four levels: completely destroyed, half destroyed, partly destroyed, and not destroyed at all. The survey also asked how long each firm experienced power outage after the GEJE. In the simulation, we utilize the information to determine the initial reduction rate of production capacity (100, 50, 25, and 0% if production facilities were completely, half, partly, and not destroyed, respectively) and the duration of production shutdowns of each firm included in the RIETI data.

## 2.4 Seismological and tsunami data

Because the number of establishments covered in the RIETI survey is far smaller than that in the TSR-Census data, we cannot identify the level of damage to production facilities and the duration of production shutdowns of all establishments in the TSR-Census data. Therefore, we estimate them using the intensity of the GEJE at the city level from the seismological data of Japan Meteorological Agency (2012) and the height of the tsunami in each $100m \times 100m$ mesh developed by Sekimoto *et al.* (2013) together with the RIETI data. For this purpose, we first examine the correlation between the level of the damage to each firm reported in the RIETI data and the intensity of the earthquake and the depth of the tsunami of the city where the firm is located taken from the seismological and tsunami data. Figures 1 and 2 show how the earthquake intensity and the tsunami height are correlated with the level of damage at the firm level. Using the probability of each level of damage to a firm given an earthquake intensity and tsunami height, we randomly assign the level of the damage to each establishment not covered in the RIETI data but included in the TSR-Census data. If an establishment is affected by both of the earthquake and the tsunami, the level of its damage is determined by the heavier damage by either the earthquake or tsunami. For example, if the estimated level of damage to an establishment by the earthquake is "half destroyed" while that by the tsunami is "completely destroyed," we assume that production facilities of the establishment were completely destroyed. Similarly, we use the relationship between the tsunami height from the tsunami data and the duration of power outage from the RIETI data and estimate the duration of power outage for each establishment included in the TSR-Census data.

## 2.5 Data on actual production after the GEJE

Finally, we need data for production in frequent intervals, rather than the yearly or quarterly gross domestic product (GDP) of Japan, to obtain parameter values that provide a better fit between the simulated and actual production. For this purpose, we utilize the Indices of Industrial Production (IIPs) (Ministry of Economy, Trade and Industry, 2022) that indicate the monthly production in the manufacturing sector as a percentage of its average in a particular year. Using the yearly GDP and monthly IIPs, we construct the total monthly value added production of Japanese firms.

# 3 Model

## 3.1 Overview and key assumptions

We employ the dynamic agent-based model at the firm level of Inoue & Todo (2019a,b, 2020), which is an extension of the model of Henriet *et al.* (2012). Although our simulation incorporate the establishment-level data in addition to the firm-level data as explained in the previous section, we use the establishment-level data mainly to estimate damage to production facilities in the disaster-hit regions. Therefore, our model is at the firm level, although the initial shock is given at the establishment level.

Each firm utilizes a fixed amount of labor and various intermediates provided by its suppliers, produces its product, and sells it to client firms and final consumers. Supply chains are a priori determined by the data and fixed over time: Even after an economic shock, such as a natural disaster, firms cannot replace disrupted suppliers or clients with new ones.

We assume a Leontief production function where factors of production, i.e., certain types of intermediate goods, labor, and electricity, are required in fixed proportions predetermined by the data. Products are industry-specific, and thus firms in the same industry produce the same product. Industries are defined by the Japan Standard Industrial Classification (Ministry of Internal Affairs and Communications, 2013). Firms hold an inventory of each intermediate good to prepare for shortage of supplies, although no inventory of service inputs or produced goods within the producer firms is assumed.

Following standard agent-based models, our model does not assume profit-maximization of firms but assumes several simple rules for demand and supply as explained in detail later. In the initial period without any shock to supply chains, or on day 0, the demand for and supply from any firm are equal to each other. At the end of day 0, a natural disaster hits some regions in the economy, and hence, production facilities in the affected regions are damaged. In addition, the supply of electricity in the affected regions is limited for a certain period after the disaster. Accordingly, the production capacity of firms affected by the disaster and power outage declines, and thus they may have to ration their products to their suppliers and consumers. Reductions in production propagates upstream and downstream through supply chains, because firms directly affect by the disaster reduce demand for inputs from their suppliers and supply to their clients.

An overview of the model is depicted in Figure 3. The source code to execute the model is on GitHub, as is the correspondence between the code and the model[6].

## 3.2 Demand and supply in the pre-disaster period

We start with the description of the economy without any supply chain disruption on day 0. In the followings, the supply of the intermediate product from supplier $i$ to client $h$ on day $t$ is denoted by $Q^S_{hi}(t)$, and the supply of firm $i$ to the final consumers is denoted by $Q^S_{Ci}(t)$. Then, the production of firm $i$ on day 0 is given by

$$Q^S_i(0) = \Sigma_h Q^S_{hi}(0) + Q^S_{Ci}(0). \tag{1}$$

Demand for products is determined in the following two ways. First, firms predicts that the demand for their product is the same as that on the previous day, $Q^D_i(t-1)$. Therefore, firm $i$ demands supplier $j$'s product of an amount $Q^S_{ij}(0)Q^D_i(t-1)/Q^S_i(0)$. Second, firms demand intermediates to stock inventories. We denote firm $i$'s inventory of the intermediate produced by firm $j$ at the beginning of day $t$ by $I_{ij}(t)$. Firm $i$ targets to restore this inventory to a level $n_i Q^S_{ij}(0)$ so that supplies for $n_i$ days are stocked. We assume that $n_i$ is randomly determined by a Poisson distribution where the mean is $n$. When the actual inventory is smaller than its target, firm $i$ increases its inventory gradually by $1/\tau$ of the gap day by day,

[6]The URL for an anonymized repository is `https://anonymous.4open.science/r/ProductionNetworkSimulator-461E`

where $\tau = 6$ following (Hallegatte, 2008). Accordingly, firm $i$'s demand for the product of its supplier $j$ on day $t$, $Q_{ij}^D(t)$, is the sum of the demand for production and inventory:

$$Q_{ij}^D(t) = Q_{ij}^S(0)\frac{Q_i^D(t-1)}{Q_i^S(0)} + \frac{1}{\tau}\left[n_i Q_{ij}^S(0) - I_{ij}(t)\right]. \tag{2}$$

By summing up the demand from all clients and final consumers, we obtain the total demand for the product of supplier $i$ on day $t$, $Q_i^D(t)$:

$$Q_i^D(t) = \Sigma_h Q_{hi}^D(t) + Q_{Ci}^D. \tag{3}$$

On day 0, we assume that the level of inventory is equal to its target level ($n_i Q_{ij}^S(0) = I_{ij}(0)$) and that the demand for the product of firm $i$ on the previous day is equal to its production ($Q_i^D(-1) = Q_i^S(0)$). Therefore, there is no excess supply or demand on day 0: $Q_{ij}^S(0) = Q_{ij}^D(0)$ and $Q_i^S(0) = Q_i^D(0)$

## 3.3 Reduction in production capacity because of a natural disaster

Suppose that a natural disaster hits some regions of the economy at the end of day 0. The disaster shrinks the production of firms in two ways. First, because the disaster causes destruction of production facilities and power outage of establishments in the affected regions, their production capacity declines. When any establishment of a firm is affected by the disaster, production of the firm declines by the amount estimated from the share of the establishment in the pre-disaster production of the firm.

In particular, we assume that establishments in the power outage regions shut down their production. The duration of the power outage for establishments is reported in the RIETI data if they are surveyed and estimated from the tsunami height otherwise. In addition, although the reported duration is more than six months for some establishments, we assume that establishments in the power outage regions recover their production fully $\xi$ days after the disaster. The value of $\xi$ is to be calibrated. This is because when the duration of the power outage is very long, suppliers and clients connected to establishments experiencing power outage may find other partners and recover production. Instead of modeling dynamics of supply chains, we simply assume the maximum duration of the power outage.

After (re)starting operation in the post-disaster period, firms' production capacity is lower than in the pre-disaster period. More precisely, the rate of reduction in the production capacity of firm $i$ in the disaster regions on day $t$, $\delta_i(t)$, is determined by a larger value among the reduction rate because of the damage to production facilities, $\delta_i^{\mathrm{f}}(t)$, and that because of power outage, $\delta_i^{\mathrm{P}}(t)$:

$$\delta_i(t) = \max(\delta_i^{\mathrm{f}}(t), \delta_i^{\mathrm{P}}(t)). \tag{4}$$

More specifically, $\delta_i^{\mathrm{f}}(1)$ is determined by the level of damage reported by the firm (establishment) taken from the RIETI survey (Section 2.3) and the seismological and tsunami data (Section 2.4), i.e., the $\delta_i^{\mathrm{f}}(1)$ is probabilistically determined by the location of firm (establishment) $i$ at the city level and the probability of each level of damage in that city given by the RIETI data, the intensity of the earthquake, and the height of the tsunami. After that, damaged production facilities recover gradually. We particularly assume that the rate of reduction in production capacity declines at the rate of $\gamma$ and a damping factor $\zeta(t)$ equal to the ratio of healthy neighboring firms to all neighbors on day $t$. The damping factor corresponds to the peer effects observed in empirical studies (Todo *et al.*, 2015). Then, the $\delta_i^{\mathrm{f}}(t)$ is expressed as follows:

$$\delta_i^{\mathrm{f}}(t) = (1 - \zeta\gamma)\delta_i^{\mathrm{f}}(t-1). \tag{5}$$

By contrast, $\delta_i^{\mathrm{P}}(t)$ is determined differently, because firms' production reduction because of power outage does not recover gradually but recovers immediately and fully when electricity comes back. Moreover, when firms are under the power outage, we assume that the firms can partly run their operation with a reduction rate of $\lambda$. Therefore, the rate of reduction in production because of the power outage for firm $i$ in areas with power outage, $\delta_i^{\mathrm{P}}(t)$, is defined as follows:

$$\delta_i^{\mathrm{P}}(t) = \begin{cases} \lambda & (t \leq \xi) \\ 0 & (t > \xi). \end{cases} \tag{6}$$

Given the two types of the rate of reduction in production (eqs. 5 and 6), the larger one is chosen as the actual reduction rate as shown in eq. 4. Accordingly, the maximum possible production of firm $i$ on day $t(\geq 1)$, $\bar{Q}_i^S(t)$, after the disaster is given by

$$\bar{Q}_i^S(t) = Q_i^S(0)(1 - \delta_i(t)). \tag{7}$$

Second, the production of firm $i$ may also be restricted by shortages of supplies from suppliers affected by the disaster. When facing shortage of supplies from supplier $j$, firm $i$ tries to mitigate it by using its inventory of the supplies and purchasing more from other existing suppliers in the same industry. The maximum possible production of firm $i$ limited by the shortage of supplies from industry-$s$ is:

$$\bar{\bar{Q}}_{i(s)}^S(t) = \frac{\Sigma_{j \in s} I_{ij}(t)}{\Sigma_{j \in s} Q_{ij}^S(0)} Q_i^S(0). \tag{8}$$

The two sources determines the maximum possible production:

$$Q_{\max i}^S(t) = \mathrm{Min}\left(\bar{Q}_i^S(t), \mathrm{Min}_s(\bar{\bar{Q}}_{i(s)}^S(t))\right). \tag{9}$$

Therefore, the actual supply of firm $i$ on day $t$ is either determined by the maximum possible production or the demand:

$$Q_i^S(t) = \mathrm{Min}\left(Q_{\max i}^S(t), Q_i^D(t)\right). \tag{10}$$

### 3.4 Demand and supply after the disaster

When the demand for firm $i$'s product surpasses its production capacity after the disaster, the firm rations its product to its client firms and final consumers because this model does not assume price adjustment, following some simple rules explained in detail in Appendix A. In brief, in this rationing process, any of the clients and final consumers obtains a positive amount of the production, whereas clients which demand less after the disaster relative to the pre-disaster demand can meet a larger portion of their demand.

Once the rationing rules determine the supply to each client, the inventory of firm $j$'s product held by firm $i$ on day $t + 1$ is updated:

$$I_{ij}(t+1) = I_{ij}(t) + Q_{ij}^S(t) - Q_{ij}^S(0)\frac{Q_i^D(t-1)}{Q_i^S(0)}. \tag{11}$$

This equation combined with equations (2) and (10) determines the demand of firm $i$ for the intermediate good supplied by firm $j$ on day $t + 1$, $Q_{ij}^D(t + 1)$, and the total demand for firm $i$'s product $Q_i^D(t + 1)$. The supply of firm $i$ on day $t + 1$, $Q_i^S(t + 1)$, is then determined by equations (7-10).

# 4 Simulations

## 4.1 Full model

The GEJE is a mega earthquake that hit the northeastern part of Japan in March 11, 2011, causing massive human and economic losses including approximately 15 thousand deaths and a loss of economic stocks (social infrastructure, houses, and facilities) of 16.9 trillion yen (Cabinet Office of Japan, 2011). To simulate how the effect of the GEJE on production propagated through supply chains, we calibrate the model in Section 3 using the data in Section 2 and estimate the parameter values in the model using the following optimization process.

To start with, our model includes the following parameters to be calibrated: the recovery rate of production capacity after the GEJE, $\gamma$; the maximum duration of the power outage in days, $\xi$; the mean of the targeted size of the inventory of intermediate products from suppliers measured by for how many days of production intermediate are stored, $n$; and the reduction rate of production capacity because of the power outage after the GEJE, $\lambda$. We further assume that the recovery rate and the mean target inventory size are sector specific and vary across three sectors, i.e., the primary, manufacturing, and service sectors. In our simulation, we experiment with a recovery rate ranging from 0.01 to 0.30 with the interval of 0.01. Similarly, we use the range and interval of experimented values of other parameters as specified in Table 1. Therefore, there are eight parameters to be calculated. Accordingly, the parameter space of the model with the full set of parameters is $6.7 \times 10^{11}$.

The initial state of each simulation run is randomly determined in the following two ways. First, the level of damage to production facilities of each establishment not included in the RIETI data but in the disaster regions is randomly determined given its location and the intensity of the GEJE and the depth of the tsunami at the city level. Second, the target inventory size of each firm is randomly determined by the Poisson distribution with mean $n$. We select three different initial states randomly and run the simulation three times for each set of parameter values. More trials with different initial states can possibly provide a more reliable fit of the model because the variance of production from the different initial states is large. However, because the parameter space is so large that a simulation run with a particular set of parameter values approximately takes several hours, we experiment with only three initial states in the optimization process.

Using a set of parameter values and three initial states, we simulate production dynamics over the three runs for 365 days after the GEJE. Then, we can compute the mean squared error (MSE) between the daily simulated and actual production. Because we rely on the monthly IIPs for the actual production, we define daily production from the IIPs and GDP simply assuming that the IIP of a month can be applied to any day in the month. Using the actual daily production, we can calibrate the model so that the MSE becomes the minimum. Note that in the calibration, it is too time-consuming to employ random or grid search in the optimization process because the parameter space is extremely large. Therefore, we use Bayesian optimization so that the parameter search is conducted more efficiently.

## 4.2 Simplified models

In addition to the benchmark model with the full set of parameters, or the full model, we simulate two simplified models to examine what factors lead to a better fit. First, we experiment with a model with only three parameters, i.e., $\gamma$, $\xi$, and $n$, following Inoue & Todo (2019a). Any of these three is not assumed to be sector specific. By comparing the result from the simplified model with that from the full model, we can examine whether and how much adding parameters improve the fit between the actual and simulated production after the GEJE. Second, we simulate another simplified model assuming no power outage after the GEJE to examine how incorporating power outage into the simulation affects the predictive power of the model. In other words, we assume $\lambda = 0$ and $\xi = 0$ and thus drop these two parameters from our simulation. The range and interval of each of the parameters used in the simplified models are the same as used in the full model.

# 5 Results

## 5.1 Optimization process

Figure 4 shows the distribution of the MSE in logs from the optimization process to search for the best parameter values using the full model. The number of sets of parameter values searched is 1,957. In the optimization process, we first experiment with 100 sets of parameter values selected randomly. In this first step, the distribution of the MSE is relatively flat because of the randomness, as indicated in the right side of Figure 4. After the first step, parameter values are chosen by an optimization algorithm in which the parameter space that generates a larger MSE than a threshold value is dropped from the further experiments. As a result, there is a large gap in counts at the logged MSE of about 2.8 in Figure 4. Moreover, counts shrink as the logged MSE becomes smaller in the left side of the figure, implying that the optimization process gradually decreases the MSE and finally finds parameter values that are close to the optimal.

Figure 5 visualizes the optimization process using the full model. More precisely, the diagonal panels in the figure show the distribution of the root MSE based on surrogate models where the value of a particular parameter changes while other parameters are averaged out. For example, the top panel indicates that the error becomes smaller as $x_0$, or the recover rate (%) for the primary sector, increases. Further assuming that the values of two parameters change while others are averaged out, the off-diagonal panels show contour graphs that indicate the distribution of the MSE by color (yellow and green indicate small and large MSE, respectively) and plots of parameter values used for simulation in black.

From the optimization process, we find that the best parameter values are 0.13 for the recovery rate of the primary sector, 0.03 for that of the manufacturing sector, 0.29 for that of the service sector, 6 for the mean target inventory size of the primary sector, 18 for that of the manufacturing sector, 13 for that of the service sector, 0.35 for the power outage loss rate, and 4 for the power outage truncate duration (days). These optimized values are shown by red lines in the diagonal panels of Figure 5 and red dots in the off-diagonal panels.

Several findings in the optimization process should be noted. First, the distribution of the MSE when we change the inventory size for the primary sector ($x_3$) looks almost flat, suggesting that this parameter does not affect the MSE substantially. Because the primary sector uses less inputs than other sectors, the size of intermediate inventory may negligibly affect the simulation results. Second, the distribution of the MSE when changing the power outage loss rate ($x_6$) and the power outage truncate duration ($x_7$) is almost flat. This finding implies that the value of the two parameters does not affect the simulation results much. We will discuss these issues in detail in the next section.

## 5.2 Comparing predictions of different models

Figure 6 shows the simulation results. The red line presents changes in the daily total value added production of Japanese firms for 365 days after the GEJE using the model with the full set of eight parameters and the parameter values that lead to the best fit with the actual production. The daily value added is averaged over the three runs with different initial states (Section 4). The green line presents the corresponding changes in value added using the simple model with only three parameters and firm-level data of Inoue & Todo (2019a). The pink bars indicate the actual production estimated from the monthly

IIPs and GDP. The MSE between the simulated and actual daily production for the full and simple models is 3.24 and 15.4 (its square root is 1.80 and 3.93), respectively. This finding suggests that the model with eight parameters can predict the actual production dynamics after the GEJE more precisely than the simple model with three parameters. In particular, Figure 6 shows that the full model can explain the large reduction in production immediately after the GEJE, possibly because the simulation of the full model incorporates damage to production facilities of non-headquarter establishments and the power outage in the disaster-hit regions and thus appropriately estimate the propagation of the shock from the disaster regions to others.

Figure 7 compares the production dynamics predicted by the full model and other models defined in Section 4.2. Panel (a) shows the comparison with the model assuming no power outage. The gap between the production dynamics from the two models indicate the production loss because of the power outage. In total, the difference between the total production predicted by the two models is 2.7 trillion yen, or 11.8% of the production loss predicted by the full model (11.8 trillion yen).

Panel (b) shows the comparison with the model with only three parameters, i.e., the recovery rate, the recovery delay, the mean target inventory size. In addition, we assume that these parameters are not sector specific, that is, all firms share the same values of the three parameters. Although this model is similar to that used in the prior study (Inoue & Todo, 2019a) presented by the green line in Figure 6, we incorporate into this model initial shocks at the establishment level, rather than at the firm level used in Inoue & Todo (2019a). The MSE given by the best solution using the model with three parameters is 3.55 (the square root is 1.88), compared with 3.24 generated by the full model. Therefore, the difference between the predictions of the two models is not quite large.

# 6 Discussion and Conclusions

This paper simulates the economic loss because of supply chain disruptions triggered by the Great East Japan earthquake (GEJE) in 2011. We particularly improve the data and model used in the previous studies (Inoue & Todo, 2019a,b) by incorporating more parameters into the model and employing establishment-level data, post-disaster survey data, and seismological and tsunami data.

The full model with eight parameters using the newly constructed data successfully improves the fit between the simulated and actual production after the GEJE, compared with the previous model in (Inoue & Todo, 2019a,b), as shown in Figure 6. There are four potential reasons for the improvement. First, assuming more parameters to be calibrated provides us more flexibility so that the predicted outcome could be closer to the actual outcome. Second, we estimate the initial economic shock of the GEJE more accurately by identifying non-headquarter establishments in the disaster-hit regions, damage to production facilities, and the duration of production shutdowns from the new data. Third, we incorporate the negative effect of the post-disaster power outage on production that was quite substantial for a few weeks after the GEJE. Finally, because we can identify indirect supply chain linkages between establishments through their headquarters using establishment-level data on firm attributes and firm-level data on supply chains, the simulation in this study can capture propagation of the economic shock through supply chains more accurately. In particular, without information on supply chains between establishments, the initial propagation from non-headquarter establishments in the disaster regions to others should be undervalued.

Among the four potential reasons, the first one, a larger number of parameters, does not seem to result in a large improvement in the predictive power, because Panel (b) of Figure 7 clearly shows that the predictions from the models with eight and three parameters are quite similar when they use the same detailed data. This finding may imply that the model with the three parameters can sufficiently explain the propagation of economic shocks through supply chains whereas the poor fit found in Inoue & Todo (2019a) relative to the fit from the full model (Figure 6) attributes to their less detailed data than ours. By contrast, we find that the third factor, i.e., incorporation of power outage, improves the predictive power to a certain extent, as shown in panel (a) of Figure 7. However, the size of the improvement is not very large, accounting for 11.8% of the total production loss. Therefore, we conclude that the improvement in the predictive power by our new simulation method is mostly due to our detailed data at the establishment level. Identifying non-headquarter establishments in the disaster-hit regions, damage to these establishments, and supply chains between establishments should have resulted in the better fit in this study.

Finally, several remarks from this study should be mentioned. First, we discussed just above a possible reason for the small improvement by adding parameters in the full model. An alternative possible reason for this is that we fail to find the optimal parameter values in our optimization process because the parameter space for the full model is substantially larger ($6.7 \times 10^{11}$) than for the model with three parameters. Conducting more experiments for further optimization may lead to a better fit.

Second, although we fit the predicted value with the total production of Japan in the optimization process, it is also possible to fit the predicted and actual values of value added production of each prefecture because the IIPs are available at the prefecture level (Figure 8). However, when we tried to do so, we found that the difference between the predicted and actual production at the prefecture level was quite large and that the sum of the differences for all prefectures is larger than the corresponding difference when we fit the predicted and actual total production of Japan. These findings contradict standard consideration that more observations help to obtain a better fit. If we could improve the model, we might be able to obtain a better fit by utilizing production at the prefecture level.

Third, the distribution of the MSE by changing the value of the loss ratio and duration of power outage ($x_6$ and $x_7$ in Figure 5) is almost flat. This indicates that the values of the two parameters may not be accurately estimated because any change in the parameter value does not improve the fit substantially and if anything, different values could lead to a better fit. The difficulty in determining the optimal value of the two parameters would have led to a bias in the simulation.

Finally, we admit that we ignore some heterogeneity among establishments and among supply chain links. For example, when firms suffer from the same level of damage to their production facilities because of disasters, the rate of reduction in production capacity of some of them may be smaller than that of others because the former prepare for such damage more than the latter. Also, some supply chain links are more robust than others because of the strength of the links backed by long-term or shareholding relationships. We leave these issues for future research.

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# Figures

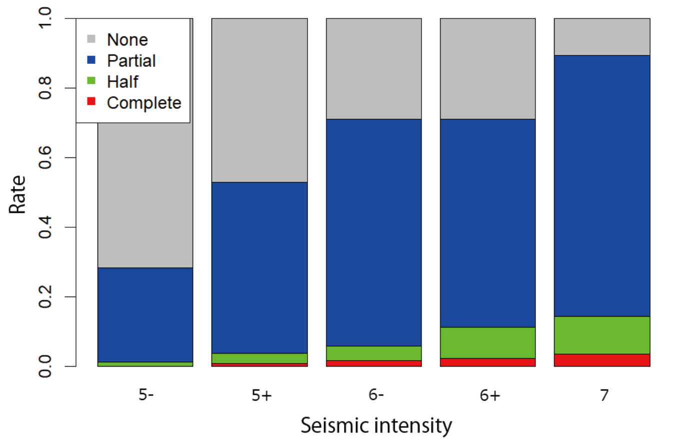



Figure 1: Seismic intensity and rate of establishment damage. Obtained from RIETI Survey and seismological data of Japan Meteorological Agency (2012).

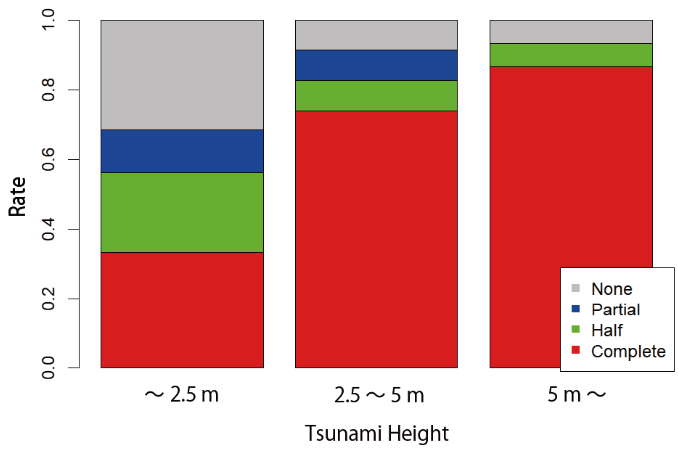



Figure 2: Tsunami height and rate of establishment damage. Obtained from RIETI Survey and tsunami data of Sekimoto *et al.* (2013)

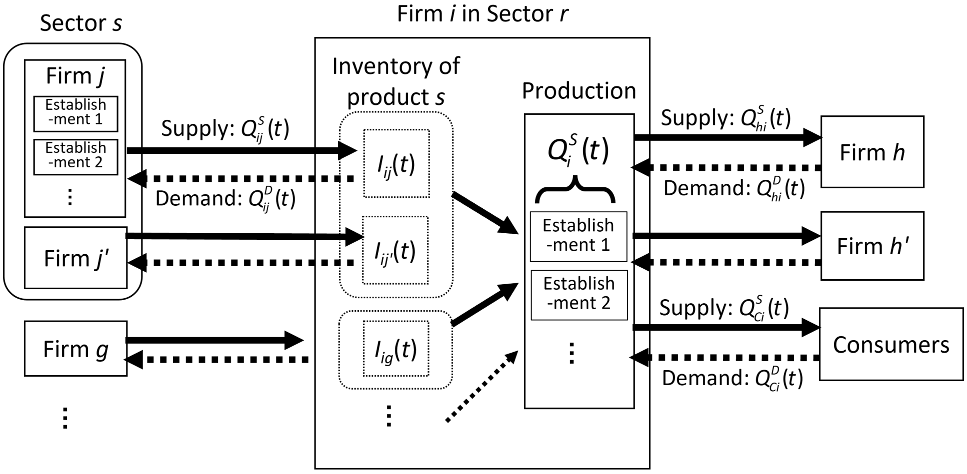



Figure 3: Overview of the agent-based model. Products flow from left to right, whereas orders flow in the opposite direction.

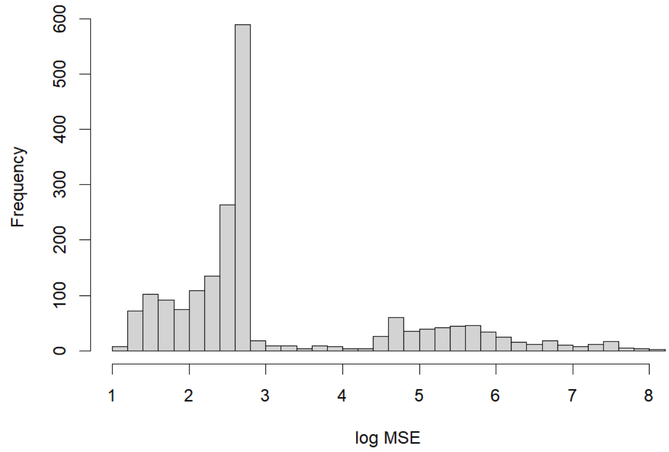



Figure 4: Error distribution of optimization process for the full model.

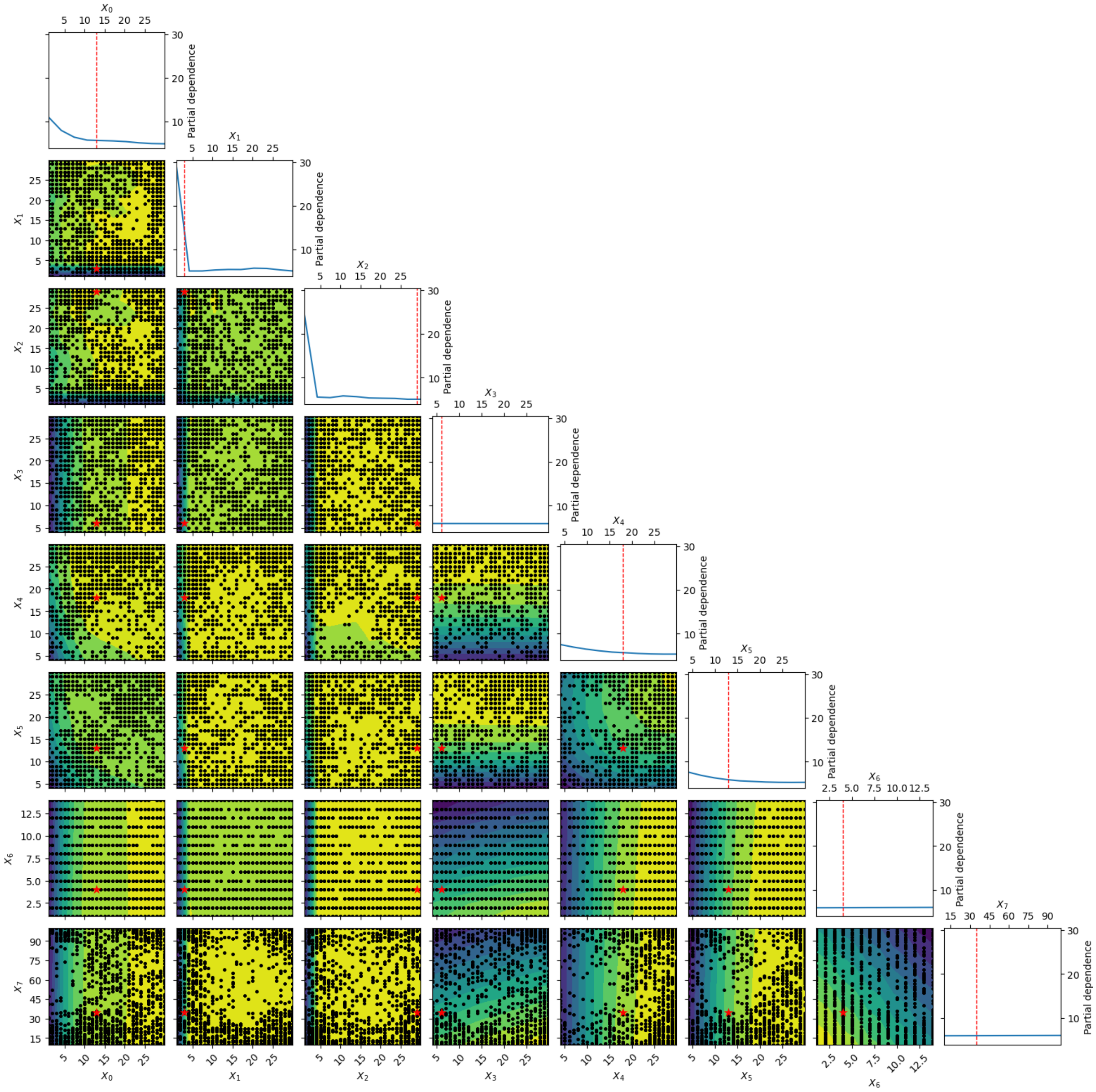


Figure 5: Optimization process for the full model. The variables from x0 to x6 indicate the recovery rate (%) for the primary sector, the secondary sector and the service sector, the inventory size for the primary sector, the secondary sector and the service sector, the power outage cutoff day, and the power outage loss rate (%), respectively. The diagonal graphs show the estimated error (Partial dependence) by a variable. Other variables are averaged out in the graphs. The panels below the diagonal panels are the contour graph and the samples plot. Black dots are samples. The colors of the contour show the error and yellow shows better (smaller) errors. This contour is drawn by the two variables estimation with averaging out other variables. The red star is the sample with the best error.

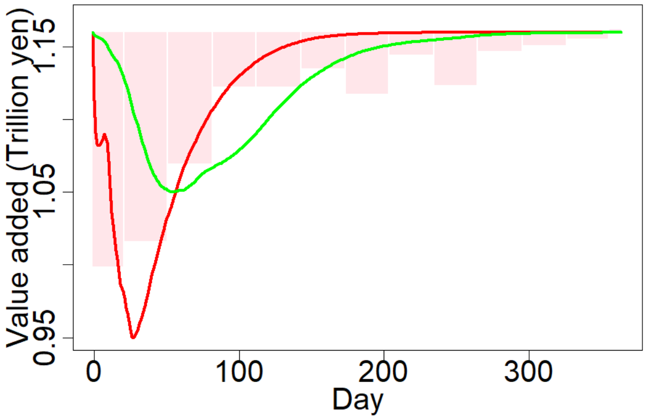
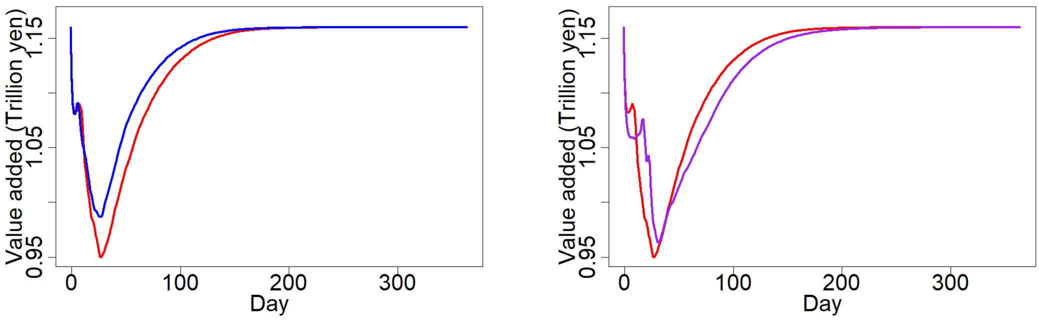



Figure 6: Calibration result and comparison with calibration in literature. The red and green line shows the result of the calibrations of this study and the literature Inoue & Todo (2019a). The horizontal axis is the day and the vertical axis is the daily value added.




(a) Full and no power outage models

(b) Full and less parameter models

Figure 7: Comparisons between calibrations of full and two other models. (a) Comparison between full and no power outage models. The red and blue lines are the calibrated full model and no power outage model, respectively. The lines are the average of 30 trials. The horizontal axis is the day and the vertical axis is the daily value added. (b) The red and purple lines are the calibrated full model and less parameter models, respectively. The lines are the average of 30 trials. The axes are the same as Panel (a).

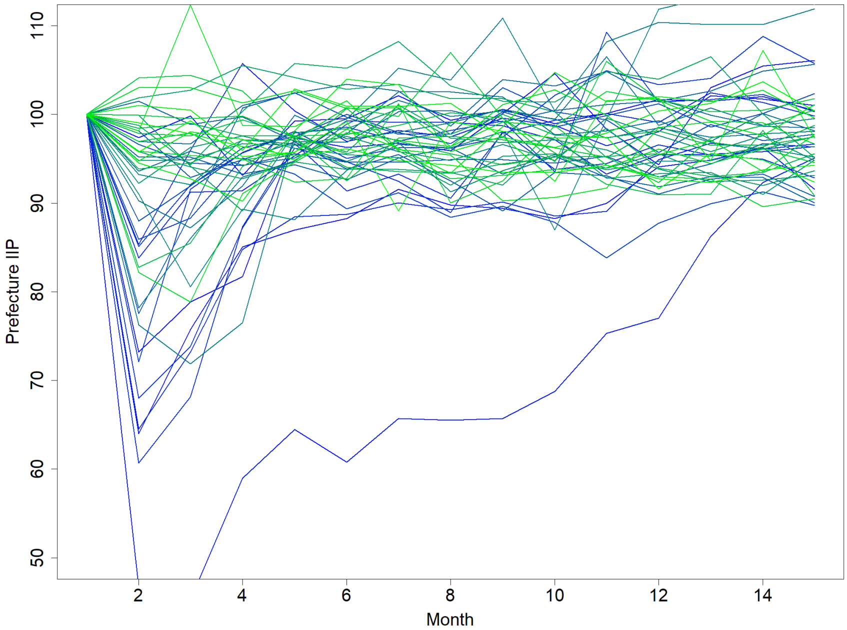



Figure 8: Prefectural Indices of Industrial Production (IIP).

# Tables

Table 1: Parameters for calibration

| Parameter | Definition | Range | Interval |
|---|---|---|---|
| $\gamma$ | Recovery rate of production capacity (sector specific) | 0.01-0.30 | 0.01 |
| $n$ | Mean target inventory size (days, sector specific) | 4-30 | 1 |
| $\xi$ | Maximum duration of power outage (days) | 4-30 | 1 |
| $\lambda$ | Reduction rate of production capacity because of power outage | 0.10-1.00 | 0.01 |

# Appendix A: Rationing Rules

To explain the rationing rules, we denote the ratio of client $j$'s demand for the product of firm $i$ to its initial demand by $q^D_{ji}(t) \equiv Q^D_{ji}(t)/Q^S_{ji}(0)$ and the corresponding ratio for the demand of final consumers by $q^D_{Ci}(t) \equiv Q^D_{Ci}(t)/Q^S_{Ci}(0)$. Then, the supply to each client and consumer is determined by the following steps. At the beginning of step $x$, the amount of production that has not been rationed and remains to be rationed is defined as $Q^R_i[x]$. We also define the minimum ratio of the current demand to the initial demand by $q^D_{\text{min}}(t) \equiv \text{Min}(q^D_{ji}(t), q^D_{Ci}(t))$. In the first step where $x = 1$ and $Q^R_i[1] = Q^S_i(t)$ by definition, if

$$Q^R_i[x] \geq q^D_{\text{min}}(t) Q^D_i(t), \tag{12}$$

firm $i$ rations to each client firm and consumer the amount of its demand multiplied by the minimum demand ration $q^D_{\text{min}}(t)$. The remaining of the production, $Q^R_i[x+1] = Q^R[x] - q^D_{\text{min}}(t)Q^D_i(t)$, is handed over to the second step. In the second step, a client firm or the aggregate consumer that satisfies its demand (or whose rate of the current demand to the initial demand is at the minimum) is dropped. By contrast, if equation (12) does not hold in the first step, firm $i$ rations to each client and consumer the amount of its demand multiplied by the ratio of the remaining production to demand defined by $q^D_{\text{r-d}i} \equiv Q^R_i[x]/Q^D_i(t)$. Accordingly, the remaining of the production $Q^R_i[x+1]$ is equal to $Q^R_i[x] - q^D_{\text{r-d}i}(t)Q^D_i(t)$ and handed over to the second step. In the further steps, we will repeat this procedure until $Q^R_i[x]$ becomes zero.