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Does visible shock update firms' unrelated trade diversity in anticipation of future shock? Evidence from the Great East Japan Earthquake and expected Nankai Trough Earthquake

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Does visible shock update firms' unrelated trade diversity in anticipation of future shock? Evidence from the Great East Japan Earthquake and expected Nankai Trough Earthquake

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ABSTRACT. This paper investigates empirically the interrelationship between the update of risk perception of expected disaster through the actual disaster damage and the change in the spatial distribution of inter-firm transactional networks (supply chains) around the hazardous area of the expected Nankai Trough Earthquake after the Great East Japan Earthquake from 2009 to 2017. By adopting the propensity score matching and the difference-in-difference (-in-differences) method, this study estimates the effects of tsunami damage on the magnitude of the spatial dispersion of the supply chain network stemmed from risk perception. The results show that the existence of suppliers in the Nankai Trough area per se did not or marginally lead to the supply chain dispersion regardless of the size of firms, while the supply chains of medium-size firms who had suppliers in both the Nankai Trough area and the damaged area of the Great East Japan Earthquake was spatially dispersed after 2011.

Keywords: Interregional trade, Supply chain, Disaster risk, Spatial pattern, Diversity

JEL code: R11, R12, Q54

1. Introduction

Modern industrial activity links organizations around the world with other organizations that produce different products. These organizations constitute the supply chain network that begins with the conception of a product and ends with its delivery (Fujita and Thisse, 2013). The supply chain network achieves efficient production by exploiting differences in technology, number of production factors, and factors among regions or countries (Feenstra, 1998). The pursuit of comparative advantage diversifies and complicates the form of the network. The geographic scope of the supply chain differs depending on, for instance, the productivity of the firms and the intra-firm trade, as well as the arm's length trade regulation, which plays an important role in the input-output linkage (Antras and Helpman, 2004). In this respect, each firm must manage a supply chain that has the capacity to adapt to complexity and diversity.

Recent investigations regarding supply chain and international trade have emphasized the importance of a comprehensive understanding of the vulnerability and resilience of the supply chain network structure to disruption or idiosyncratic shock (see Bernard and Moxnes, 2018). Such shocks include natural disasters, industrial disputes, and terrorism, and appropriate supply chain response can ensure a sustainable supply chain and continuous industrial activity. As mentioned in Barrot and Sauvagnat (2016), the supply chain network responds to shocks in two ways: on the one hand, shocks can be absorbed in the network since firms organize their operations to reduce any damage by recomposing their production mix or switching to other suppliers; on the other hand, shocks can propagate from firm to firm through the network and be amplified because the switching costs for replacing suppliers could prevent firms from making adjustments during disruption. Recent empirical investigations have examined such mutually contrasting behaviors by analyzing the propagation of economic loss, the structural change of a supply chain network, and the recovery of firm performance after localized, huge natural disasters. In terms of the risk management of natural disasters, the importance of pre-disaster planning in the supply chain network as well as post-disaster recovery has been emphasized in recent years (e.g., Ranghieri, and Ishiwatari, 2014; Fujita, Hamaguchi, and Kameyama, 2018) as recent natural disasters have revealed the vulnerability of the supply chain network to unexpected disruptions. Thus, damage in the supply chain network has been recognized increasingly as a primary cause of a disaster's economic damage. Christopher (2016) mentions factors underlying the supply chain network's vulnerability such as supply chain globalization, focused factories and centralized distribution, and a reduced supplier base. Thus, pre-disaster preparation eliminating these factors by means of, for instance, the diversification of suppliers, relocation to low risk regions, and the development of a business continuity plan, has been regarded as one of the pressing necessities for every firm's operations.

A growing awareness of pre-disaster preparation is related to discussions of risk. That is, disaster shocks can change the perceived risks associated with hazard facilities (Zhu, Deng, Zhu, and He, 2016) or hazardous areas (Naoi, Seko, and Sumita, 2009). Recently, the economic impact of hazardous facilities and regions has generated a growing body of literature. In the context of urban economics, for example, changes in risk perceptions generated by an unexpected disruption can be measured by the price effect in the real estate market in proximity to the hazardous facilities or the hazardous area. However, as far as I can gather, little is known about the impact from disaster shocks on the change in risk perceptions in the supply chain network based on rigorous econometric evidence rather than anecdotal evidence.

This paper examines the impact of changes in risk perceptions on the supply chain network after observed disaster damage in terms of pre-disaster preparation by investigating the Great East Japan Earthquake in 2011 and the expected Nankai Trough Earthquake, the forthcoming mega earthquake in West Japan, as examples of actual and visible disaster shock and fiture disaster shock, respectively. Through an examination of the choices of the firms surrounding the damaged area of the East Japan Earthquake and the hazardous area of the expected Nankai Trough Earthquake after 2011, this study attempts to show to what extent risk perception can serve as the driving force in pre-disaster preparation in the supply chain network and how firms form the supply chain network structure based on these perceptions under various constraint conditions. The exploration of this issue based on both the Great East Japan Earthquake and the Nankai Trough Earthquake is notable because of the similarities of the situations of these earthquakes. The damaged area around the Great East Japan Earthquake included an atomic-power accident, a tsunami, as well as ground movement, which caused heavy damage to large areas all over Japan. Similar damage is expected in the Nankai Trough hazardous area.

One of the unique features of risk perception in the supply chain in comparison with the real estate market is the existence of a tradeoff in pre-disaster preparation strategy. That is, when firms are motivated to create a disaster plan based on their risk perception, they may face the following dilemma. On one hand, the intensive supply chain network can reduce the daily transaction cost while it could prevent them from switching to alternative suppliers and decreases the absorption ability to alleviate shocks on particular sector or region. On the other hand, the extensive supply chain network increases the absorption ability whereas it could increase daily transaction cost and the likelihood of their facing disruption. Thus, this paper adds to the discussion on how firms behave in the supply chain network under this tradeoff, as well under capacity constraints and uncertainty.

The rest of this paper is organized as follows. Section 2 reviews the literature regarding the economic impacts of natural disasters and diversification in economic activities. Section 3 briefly describes the Great East Japan Earthquake in 2011 and the expected Nankai Trough Earthquake and the (assumed) damage from each earthquake. Section 4 describes the dataset and the analytical framework of the impact evaluation. Section 5 reports the estimation results. Section 6 concludes.

2. Literature Review

2.1 Natural disasters and firms' activities

Here, natural disaster impact studies related to the issue are reviewed. As summarized by Xiao (2011), studies on this topic take two general directions: a simulation modeling approach[1] and an empirical assessment approach. Since an empirical assessment approach looking at firm-level data is used in this study, the literature review focuses mainly on such impact studies[2]. The empirical assessment of the impact of a natural disaster on the supply chain using firm-level data has followed two perspectives in recent years.

On the one hand, several studies have pursued impact evaluations focusing on the magnitude of the effects of the damage and the recovery from the natural disaster on firm performance. As in several earlier investigations, Altay and Ramirez (2010) examined the impact of over 3,500 disasters on more than 100,000 firm-year observations over 15 years and found that the effect of floods depends on the position of each firm in the supply chain. That is, floods seriously damaged the downstream firms, whereas the upstream firms remained undamaged. De Mel, McKenzie, and Woodruff (2012) investigated the effects of relief aid and access to capital in the recovery of Sri Lankan microenterprises after the 2004 tsunami. They found that the role of capital in the manufacturing and services sectors recovery was limited by disruptions in the supply chains. Further, recent studies have incorporated explicitly the

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[1] Recent studies based on simulation modeling of the expected Nankai Trough earthquake using input-out (IO) economics and the computable general equilibrium (CGE) approach are comprehensively reviewed in Tokunaga and Resosudarmo (2017). As a primary investigation involving another simulation approach, Inoue and Todo (2017) examined how negative shocks due to natural disasters, for example, propagate through supply chains. They applied an agent-based model to actual data in the supply chains among Japanese firms and found that the direct damage of the expected Nankai Trough Earthquake would be approximately 12 times that of the Great East Japan Earthquake.

[2] Regarding natural disaster impact studies based on an empirical approach not limited to firm-level analysis, the reviews by Cavallo and Noy (2011) and Kousky (2014) provide comprehensive perspectives on the recent trends in the literature.

structure of the supply chain, mainly based on transactional network data and arrived at more detailed implications regarding the economic impact of natural disasters.

Here, several investigations that incorporate the structure of the supply chain are reviewed. Todo, Nakajima, and Matous (2015) examined how supply chain networks affected the recovery of firms after the Great East Japan Earthquake. They found that networks with firms outside of the damaged area contributed to production recovery, whereas networks within the region contributed to sales recovery in the medium term. Barrot and Sauvagnat (2016) examined whether firm-level idiosyncratic shocks associated with the natural disasters propagate in production networks. They showed that affected suppliers impose substantial output losses on their customers, especially when they produce specific inputs. Carvalho, Nirei, Saito, and Tahbaz-Salehi (2016) estimated the overall macroeconomic impact of the shock by incorporating the aftermath effects that the earthquake propagates for both upstream and downstream supply chains, affecting the direct and indirect suppliers and customers of disaster-stricken firms. They found that the propagation over input-output linkages accounted for a 1.2 percentage point decline in Japan's gross output the year after the Great East Japan Earthquake. Boehm, Flaaen, and Pandalai-Nayar (2018) examined the cross-country transmission of disaster shock and showed that the output of Japanese affiliates in the U.S. fell after the Great East Japan Earthquake. Kashiwagi, Todo, and Matous (2018) examined how the sales growth of firms inside and outside the United States changed when their suppliers or clients were damaged by the hurricane in 2012 in the United States. They showed that the effect of damaged firms on their United States' transactional partners was negative and statistically significant, but not true for their partners outside of the United States.

On the other hand, impact evaluations focusing on the choice of pre-disaster or post-disaster business activities based on the supply chain, particularly related to the issue here, have been accumulating as well. Todo, Nakajima, and Matous (2013) examined the relationship between the number of transaction partners and the probability of supplier changes in the case of the Great East Japan Earthquake. They found that a large number of transactional partners located in the damaged area increased the likelihood of supplier changes, whereas a large number of clients located outside the damaged area decreased the probability. Ono, Miyakawa, Hosono, Uchida, Uchino, and Uesugi (2014) examined whether and how the presence of incumbent transaction partners affected the relocation choice of damaged firms after the Great East Japan Earthquake. They found that firms tended to move to areas where their customers were located but not to areas where their suppliers were located. Zhu, Ito, and Tomiura (2016) identified the macro fluctuation of firms' offshoring using the Great East Japan Earthquake as the exogenous shock and showed that the positive effect of the earthquake was seen in manufacturing offshoring, but not seen in service offshoring. Cole, Elliott, Okubo, and Strobl (2017) examined the extent to which pre-disaster planning and post-disaster aid played a role in firms' recovery from the Great East Japan Earthquake. They found evidence to suggest that post-disaster sales were influenced by pre- and post-disaster policies. That is, pre-disaster policies, such as having alternative transport arrangements and a diversified supplier network, positively affected post-disaster sales recovery.

As described, most recent empirical investigations related to impact evaluations of the choice of pre-disaster or post-disaster business activities associated with the supply chain have examined the impact from the perspective of post-disaster only. Thus, few empirical studies have examined in-depth the actual change in the activities of the firms looking to reduce their risks of natural disasters before a forthcoming disaster shock. Although Cole et al. (2017) looked empirically at the implication that pre-disaster policies affect post-disaster firm performance, the further question of whether pre-disaster planning in the supply chain network was instigated after actual and visible shock, the Great East Japan Earthquake, still needs to be answered[3]. This can be answered under the presumption of the occurrence of the Nankai Trough earthquake.

2.2 Diversification in economic activities

As mentioned above, one of the main measures against supply chain disruption is the diversification of supply chain. Not limited to the diversification of supply chain, the importance of diversification in economic activities has been particularly discussed in the literature. As described in, for example, Rugman (1979) and Fujita and Thisse (2013), unrelated diversification between sectors or regions can enable firms or regions to alleviate a shock on particular sector or region by avoiding the dependence on single market. This kind of function that unrelated diversification has can be similar to the portfolio theory such as CAPM. This conceptual framework has generated a growing body of empirical literature, especially in the context of economic geography[4] and international management[5].

The literature of economic geography mainly focused on the role of unrelated industrial diversity which each region has. Baldwin and Brown (2004) firstly constructed theoretical

[3] There have been several studies regarding the pre-disaster impact on the housing market caused by a huge disaster outside the regions. On the one hand, Bauer, Braun, and Kvasnicka (2017) found that housing prices near nuclear power plants that were operating at the time of the Fukushima disaster fell by almost 5% after the disaster in Germany. In addition, Zhu et al. (2016) estimated the effects of the same accident on land prices near nuclear power plants in China. They found that land prices within 40 km of nuclear plants dropped by about 18% one month after the accident. In the case of Japan, Naoi et al. (2009) found that the price discount from locating within a quake-prone area was significantly larger soon after the Great Hanshin-Awaji Earthquake in 1995. On the other hand, Ando, Dahlberg, and Engström (2017) explored the potential effect of the same accident on housing prices in Sweden and did not find any disproportionate effect from the accident.

[4] De Goort, Poot and Smit (2016) reviewed the statistical evidence of agglomeration externality including specialization, diversification and competition effects by means of 73 scientific articles.

[5] The benefit of supply chain diversification has been theoretically investigated in the literature of management science and operations research. For example, Gurnani, Mehrotra, and Ray (2011) reviewed the theoretical foundation of supply chain design under uncertainty based on microeconomics and game theory.

framework based on portfolio theory by Sharpe (1970) which explains industrial volatility in a region represented with the variance of each industry' growth, and they implied that increasing diversity will reduce volatility, but the effectiveness of diversification will decrease as the correlation among industry growth rates increases. Based on this theoretical prediction, they empirically showed the robust negative association between industrial specialization measured with the Herfindahl-Hirschman Index and the variance of industrial growth in for large regions but not for small regions with Canadian data. This result implies that whether the profit of diversification can be experienced or not can depend on the size of regions. Frenken, Van Oort and Verburg (2007) showed the negative association between cross-sectoral diversification of NUTS-3 level regions (unrelated variety) measured with entropy measure in the Netherlands and unemployment growth. This result can imply that regions with higher unrelated variety, in other words, the absorption ability against a shock experience lower rate of unemployment growth. On the other hand, with Italian NUTS-3 level data, Boschma and Iammarino (2009) did not find statistically robust association between economic growth and industrial diversity of import, as well as that within region. More recently, Fritsch and Kublina (2017) investigated the association between employment growth and unrelated variety interacted with R&D intensity or that interacted with start-up rate with West German data. They showed positive association between employment growth and these interactions which can imply that high absorptive capacity combined with intensive R&D activities or new business formation can contribute to regional employment growth.

The literature of international management mainly focused on the role of both industrial and regional unrelated diversity of firms' export destinations or subsidiaries. Nachum (2004) investigated the impact of the industrial and geographical diversification activities of developing country firms on their performance and showed positive but non-linear association between the ratio of profits to sales and both industrial and geographical diversity of export destination measured with HHI. Qian, Li, Li, and Qian (2008) confirmed this curvilinear effect on firm performance which regional diversity measured with entropy measure based on the geographical distribution of firms' subsidiaries. This curvilinear effect implies that internationally connected firms operate based on some optimal point which gives the moderate number of trade origins or destinations to maximize their profit. Although Cole et al. (2017) mentioned above did not focus on international trade but domestic trade, their investigation can be also categorized in this literature in the sense that they examined the association between regional diversification of transaction partners and business recovery.

Despite the growing body of empirical literature examining the association between unrelated diversity and economic performance of firms or regions, little is known about what can form the diversity per se. One of the few investigations is Kamal and Sundaram (2019). They examined causal effect of country-level institutional quality on patterns of spatial concentration of global sourcing and showed that the extent to which U.S. importers source became more spatially concentrated under weaker contract enforcement, since the existence of local supplier networks who serve as facilitators of matching and transactions matters more to avoid high transaction costs and frequent losses due to uncertainty. This study complements this literature by examining alternative and opposite consequence on spatial pattern of transaction or trade under uncertainty, network diversification to mitigate a shock. In this study, therefore, I utilize the occurrence of the Great East Japan Earthquake as an exogeneous driver and determinant of regional trade diversification toward the risk prevention.

3. The Great East Japan Earthquake and the Nankai Trough Earthquake

The Great East Japan Earthquake in 2011, also called “3.11”, and the expected Nankai Trough earthquake and the (assumed) damage from each earthquake are briefly described here.

The characteristics of the Great East Japan Earthquake are summarized based on information from Japan’s Cabinet Office (CAO, 2011). The earthquake occurred on March 11, 2011 with a magnitude of 9.0. It caused extensive damage over a wide range centered on the northeast coast of Japan as well as widespread disruption all over Japan due to both huge ground shifts and the tsunami, with a loss of 22,626 lives and economic losses reaching 16.9 trillion yen. In addition, the meltdown accident at the Fukushima Daiichi Nuclear Power Plant from the huge tsunami led to the evacuation of 146,520 residents within 30km of the plant. The greatest difference in this earthquake in comparison with other recent natural disasters, such as Hurricane Katrina in 2005 in the United States and the Great Hanshin-Awaji Earthquake in 1995 in the southern part of Hyogo Prefecture in Japan, is the economic damage propagated in a wide sphere outside of the damaged area through the restriction of electricity and the supply chain disruption.

After the Great East Japan Earthquake, the potential risk of a substantial earthquake in the Nankai Trough area began to receive considerable attention as well. The Nankai Trough has created large earthquakes in 100- or 200-year intervals over the past 1400 years. As 70 years have passed since the last earthquake in that area (the Showa Nankai Earthquake in 1946), it has been assumed that the next huge earthquake will be within a shorter period. Although it is difficult to predict exactly the geographic scope of a large ground shifting with current technology, the rough estimation of maximum seismic intensity (see Figure 1) shows that the damage of ground movement could spread through a wide area all over Japan. According to the Cabinet Office, (CAO, 2016), the economic loss from a Nankai Trough earthquake could reach approximately 220 trillion yen. This estimated economic loss exceeds that of the Great

East Japan Earthquake, which was approximately 16.9 trillion yen, since the earthquake hazardous area is in the Pacific belt zone. In addition, the hazardous area of the expected Nankai Trough earthquake in the Shizuoka Prefecture, one of the prefectures assumed to be vulnerable to the most damage from such an earthquake, has a nuclear power plant (the Hamaoka Nuclear Power Plant). In this respect, as in the case of the Great East Japan Earthquake, a Nankai Trough earthquake may result in a complex disaster that includes tsunami damage and a nuclear plant accident as well as ground movement.

The geographical range of tsunami damaged regions of the Great East Japan Earthquake and tsunami hazardous regions of the Nankai Trough Earthquake is shown in Figure 2.

4. Methodology

4.1 Inter-firm Transaction Data

The inter-firm transaction database was provided by Teikoku Databank (TDB), a major corporate credit research company in Japan that collects inter-firm transactional data through door-to-door surveys. Around 1700 field researchers visit and interview firms to obtain corporate information in every industrial category and location. The database also includes the annual transactional relationships among the firms. During the period 2008 to 2017, the database included 39,568,392 records of transaction relationships among 1,554,850 firms. Specifically, in 2016, the database included 1,136,203 firms out of a total of 3,856,457 firms in Japan, according to the latest Japanese Economic Census in 2016. Thus, during this time, the database captured inter-firm transactional activities for nearly one-third of all firms in Japan. In addition, the dataset was connected with a corporate information database, COSMOS, so basic corporate information of each firm, such as sales, number of employees, geographic location of its headquarters, and industrial category, was also available. In the door-to-door interviews, each firm reports up to five of their suppliers and clients. Since this dataset eventually includes both self-reported and other-reported transaction information, the number of suppliers for each firm usually exceeds five. This annual data is superior as they capture the dynamism of the disaggregated supply chain network structure unlike an IO table[6].

This study focuses on the structural change of the supply chain network among firms in the context of geography. The inverse of the Herfindahl-Hirschman Index (HHI) is used as the index to measure the geographic distribution of the supply chain network. While the HHI is a

[6] Other limitations of the database are as follows: First, the database only covers the domestic supply chain network and does not capture the global scale. To consider the effect on the global supply chain, combining the database with other databases would enable the international transaction relationships to be captured. Second, the database only captures the existence of ties among firms and does not capture the transaction amounts.

well-known index for measuring market concentration, the inverse of the HHI is known as the Inverse Simpson Index in biology (Magurran and McGill, 2011) and is used to measure the diversity of species[7]. In addition, recent empirical investigations regarding agglomeration economies (see De Goort, Poot, & Smit 2016) have employed this index to measure the urbanization of economies. The HHI of the supply chain network is defined here as follows:

$$HHI_i = \sum_{j=1}^{n} \left[\frac{\left(\#of\ suppliers\ in\ region_j\right)_i}{(total\ \#of\ suppliers)_i} \right]^2, \tag{1}$$

where # represents "number;" i, j denote firm and region, respectively. In this study, 1/HHI is calculated at the prefectural level and Koiki (wide-regional plan) area[8] level.

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[7] The alternative index frequently used in the literature of economic geography to measure dispersion or concentration based on compositional data can be entropy index. Qualitative interpretation based on obtained results using 1/HHI as an outcome shown in following sections are basically consistent even if I use entropy measure as an outcome.

[8] The 47 prefectures in Japan are categorized into 10 regions based on the National Spatial Planning Act. This act aims to promote the socioeconomic development of a wide area by including several prefectures in a comprehensive, integrated manner.

4.2 Empirical Procedure

4.2.1 Conceptual Framework

Referring to the literature review in the previous chapter and the following several lines of the theoretical and anecdotal evidence, I set up following hypotheses. H1 stems from the update of firms' risk perception regardless of the direct damage on their relatives, whereas H2 stems from the update incurred by their relatives' damage.

H1: The geographical diversification of the supply chain network has been instigated toward the Nankai Trough Earthquake after the Great East Japan Earthquake, 3.11, if a firm had suppliers in hazardous regions of the Nankai Trough Earthquake before 3.11.

H2: The intensity of diversification described in H1 has been stronger if a firm had suppliers in both hazardous regions of the Nankai Trough Earthquake and damaged area of 3.11.

To assess these hypotheses, several issues regarding structural changes in the supply chain network are discussed: the motivation and the likelihood of changes in the network structure; and, which firms are more likely to be affected by the consequences of the structural changes when a natural disaster actually occurs. As mentioned, Todo et al. (2015) showed that networks with firms outside of the damaged area contributed to the production recovery; Cole et al. (2017) found that pre-disaster policies, like a diversified supplier network, positively affected post-disaster sales. These results imply that such pre-disaster strategies can improve firm resiliency in the case of disaster. Thus, this might be reflected in the direction of pre-disaster planning if firms potentially affected by the expected Nankai Trough earthquake have learned from the Great East Japan Earthquake.

Although there is little rigorous econometric evidence about the extent to which the structure of supply chain networks changed after the Great East Japan Earthquake, except in Todo et al. (2013), there is anecdotal evidence. As descriptive evidence, according to TDB

(2018),[9] 44.9% of all firms that sent effective responses, about 4,500, had already developed business continuity plans (BCPs) or were developing or investigating them. Of them, 69.1% assumed a natural disaster as a potential risk in their business activities and as a specific plan in their BCP; 35.0% of them mentioned the dispersion of suppliers and 20.8% mentioned the securement of alternative suppliers or clients. In addition, Fujita et al. (2018) provided anecdotal evidence of risk reduction activities among firms affected by the Great East Japan Earthquake. Several major manufacturing firms damaged by the Kumamoto Earthquake, such as Sony and Aisin, that had their production bases in a damaged area, recovered effectively because they implemented steps in their BCPs that included the relocation of factories to other firms and the import of alternative products from overseas plants after the Great East Japan Earthquake.

[9] The Survey on Corporate Attitudes toward the BCP (事業継続計画（BCP）に対する企業の意識調査, in Japanese) was conducted by TDB all over Japan in May 2018, targeting 2,3156 firms. A total of 10,001 effective responses were received (i.e., the response rate was 43.2%). This survey asked the firms questions such as whether they had already developed a BCP, the potential risks they assumed, specific plans included in the BCP, the effects of the BCP if they had already developed BCPs, or the reason why they had not developed a BCP.

4.2.2 Estimation Methods

In the empirical analysis, the damaged areas in the Great East Japan Earthquake were defined in terms of the municipalities that were damaged by the tsunami. The source of this information was the Ministry of Agriculture, Forestry and Fisheries (MAFF, 2011). Similarly, the Nankai Trough hazardous area was defined according to the municipalities designated as the "Areas for Special Reinforcement of Nankai Trough Earthquake Tsunami Evacuation Measures" based on "The Act on Special Measures concerning Advancement of Countermeasures against Disasters of Tonankai and Nankai Earthquakes." The source of the information was Japan's CAO (2015).

I implement comparative analysis using difference-in-differences method (DD) for examining H1, and difference-in-difference-in-differences method (DDD) for H2 based on panel data from 2009 to 2017. In following empirical analysis, only manufacturing firms whose number of suppliers is positive, and located in neither hazardous regions nor damaged regions throughout the period, are included in panel data. Referring to Angrist and Pischke (2009) and Baum-Snow and Ferreira (2015), the specification corresponding to DD is as follows:

$$[1/HHI]_{it} = \rho_t + \kappa_i + NT_i \times After_t \beta + \mathbf{x'}_{it}\boldsymbol{\delta} + \varepsilon_{it}, \tag{2}$$

where i and t denote the firm and year, respectively; $[1/HHI]_{it}$ is the inverse of the HHI regarding the supplier, as defined previously, of firm i in year t, ρ_t and κ_i are the time fixed effect and the firm fixed effect, respectively, $\mathbf{x}_{it}$ is a vector of control variables including two-digit standard industrial classification dummies, based on the TDB Standard Industrial Classification[10], Koiki area (wide-regional plan areas) dummies, industry-year dummies, and Koiki-year dummies. $NT_i \times After2011_t$, the regressor of interest, captures the effect of the Great East Japan Earthquake on the diversification of the network regardless of the direct

[10] Available in https://www.tdb.co.jp/lineup/pdf/tic.pdf.

damage on their relatives. NT_i equals 1 if firm i had suppliers in hazardous regions of the Nankai Trough Earthquake in 2008. The $After_t$ dummy indicates the post-3.11 period, namely, if $t \geq 2011, After_t$ equals 1. In a similar way, referring to Wooldridge (2010), the specification for DDD is as follows:

$$[1/HHI]_{it} = \rho_t + \kappa_i + NT_i \times EJ_i \times After_t\theta + \mathbf{z}'_{it}\boldsymbol{\eta} + \nu_{it}, \quad (3)$$

where $\mathbf{z}'_{it}\boldsymbol{\eta} = \mathbf{x}'_{it}\boldsymbol{\delta} + NT_i \times After_t\beta_1 + EJ_i \times After_t\beta_2$. $NT_i \times EJ_i \times After_t$, the regressor of interest, captures the effect of the Great East Japan Earthquake on the diversification of the network with the direct damage on their relatives. EJ_i equals 1 if firm i had suppliers in damaged regions of the Great East Japan Earthquake in 2008.

This study adopts propensity score matching (PSM) to control for selection bias (Imbens and Rubin, 2015). Taking comparative analysis on H2 as an example, the likelihood that a large firm is included in the treatment group in 2008 becomes higher since large firms tend to have a geographically broad supply chain network structure. In addition, about both H1 and H2, whether firms have suppliers in each damaged or hazardous regions or not highly depends on their location. This imbalance between the treatment group and the control group due to, for example, location, size, and sector of firms causes the problem of selection and makes the estimation with DD and DDD biased. PSM tackles this problem by matching each firm in the treatment group with a firm in the control group that has a near probability of being assigned to the treatment group. The probability of the assignment, equivalent to the propensity score, is predicted with information from the year immediately before the treatment of each firm. Thus, the PSM aims to achieve covariate balancing between the groups. In this study, the propensity score is estimated by using the logarithm of sales, the logarithm of number of employees, interaction of these variables, Koiki area dummies, and 2-digit level industrial dummies, and interaction term between continuous variables and dummy variables in 2008.

5. Results

5.1 Propensity Score Matching

In advance of the parameter estimation with DD and DDD, the attributes between the treatment group and the control group are calibrated with the propensity score matching. As the first step, I balance observable covariates between firms corresponding to $NT_i = 1$ and those corresponding to $NT_i = 0$, regarding the existence of suppliers in hazardous regions of the Nankai Trough Earthquake as a treatment. After that, as the second step, I additionally balance observable covariates between firms corresponding to $EJ_i = 1$ and those corresponding to $EJ_i = 0$, regarding the existence of suppliers in damaged regions the Great East Japan Earthquake as a treatment. The matching method used in the first step is simple one-by-many matching based on genetic algorithm (Leite, 2016), while that used in the second step is the propensity score stratification. The propensity score stratification creates subclasses of similar subjects, for example, as defined by quintiles of the propensity score distribution (Stuart, 2010). Rosenbaum and Rubin (1985), for example, demonstrated that by creating five propensity score subclasses, at least 90% of the bias in the estimated treatment effect was removed. The reasons why I utilize stratification method are as follows. First, there can be particular necessity of the control on the heterogeneous effect of the Great East Japan Earthquake depending on firm size, location, and sector. Second, it is quite difficult to keep covariate balance implemented in the first step when utilizing other matching methods. Based on this method, samples matched in the first stage are classified into five subclasses depending on the magnitude of the propensity. In this process, samples that do not satisfy the common support assumption are discarded.

Estimation results of the propensity score corresponding to each treatment status are shown in Table 1 and 2. It can be confirmed that firm size is a crucial determinant of the assignment to treatment group while the magnitude of association between the assignment and firm size is heterogeneous depending of firms' location. The results of PSM evaluated with chi-square overall test are shown in Table 3 and 4[11]. Table 3 evaluates overall covariate balance between firms corresponding to $NT_i = 1$ and those corresponding to $NT_i = 0$, while Table 4 evaluates that between firms corresponding to $EJ_i = 1$ and those corresponding to $EJ_i = 0$. The sequential serial number of each subclass is based on in ascending order of the magnitude of the propensity score. That is, firms included in Subclass 1 have smallest propensity score while those in Subclass 5 have largest one. From these results, overall covariate balance is not achieved in Subclass 1 about both NT and EJ at least 1% level. Thus, following empirical analysis is implemented on subclasses except for Subclass 1 owing to potential violation of parallel trend in DD and DDD.

As shown in Figure 3, both logged number of employees and logged sales are proportional to the magnitude of propensity score. Based on Table 5, on average, Subclass 2 includes SMEs, Subclass 3 includes medium-size firms, Subclass 4 includes large firms, and Subclass 5 includes leading firms. The spatial distribution of the firms included in each subclass is shown in Figures 4. Firms included in each subclass are commonly concentrated around Tokyo. In this sense, based on the property of dataset, the likelihood that firms' headquarters were (or will be) directly damaged by tsunami can be relatively low. Meanwhile, the intensity of concentration is stronger in Subclass 4 and 5 but not in Subclass 2 and 3. Therefore, taking account of the size of firms in each subclass, the interpretation on empirical result about Subclass 5 (or even 4) can require close attention because there can be a concern about the gap between the location of headquarters and that of business enterprises. Table 6 shows the number of firms in each treatment status.

[11] The balance of each individual covariate is provided upon request.

5.4 Regression Results with DD

In this section, I describe the estimation results with DD for examining H1. First, the results using the prefecture level 1/HHI as an outcome are examined. As shown in Tables 7, except for Subclass 5 which consists of leading firms, treatment effect in each subclass is not statistically significant. Thus, positive effect on network diversity averaged throughout the period after 3.11 is hardly observed for most subclasses. I also estimate DD based on the specification which replaces time-invariant treatment variable with time-variant treatment variables. The estimation results with time-variant treatment variables are shown in Figure 5. As is the case with averaged treatment effect, treatment effects evaluated on each year separately are not or marginally statistically significant. Although positive effects can be observed about Subclass 5, they are significant only 2011 and 2016. Thus, there cannot be consistent positive effect on network diversity in Subclass 5. Treatment variable in 2010 is not statistically significant in all subclasses, so this result implies that there cannot be a convincing evidence of violation of parallel trend.

Second, the results using the Koiki region level 1/HHI as an outcome are examined. As shown in Table 8, treatment effect in Subclass is positively but weakly significant in Subclass 5, but not in other subclasses, and even negatively significant in Subclass 2. Thus, positive effect on network diversity averaged throughout the period after 3.11 is indeed hardly observed for most subclasses. As with the estimation based on prefecture level 1/HHI, I also implement DD based on time-variant treatment variables, and obtained results are shown in Figure 6. Statistically significant treatment effects can be observed in Subclass 2 and 5, but they exposed after four or five years of 3.11. Thus, with these results, it can be difficult to assert direct causality between 3.11 and network diversity or concentration. Treatment variable in 2010 is not statistically significant in most subclasses. In Subclass 3, whereas treatment variable in 2010 and 2011 are statistically significant, the temporal variation of treatment effects is not so large compared with those after 2012. These results imply that there cannot be a convincing evidence of violation of parallel trend.

5.5 Results with DDD

In this section, I describe the estimation results with DDD for examining H2. First, the results using the prefecture level 1/HHI as an outcome are examined. As shown in Tables 9, in Subclass 3 which consists of medium-size firms, treatment effect is positive and statistically significant in 5% level, but not in other subclasses. Thus, positive effect on network diversity averaged throughout the period after 3.11 is limitedly observed. I also estimate DDD based on the specification which replaces time-invariant treatment variable with time-variant treatment variables. The estimation results with time-variant treatment variables are shown in Figure 7. As is the case with averaged treatment effect, treatment effects evaluated on each year separately are statistically significant only in Subclass 3. However, unlike the case of DD, in Subclass 3, consistently positive treatment effects can be observed relatively soon after 3.11. Treatment variable in 2010 is not statistically significant in all subclasses, so this result implies that there cannot be a convincing evidence of violation of parallel trend.

Second, the results using the Koiki region level 1/HHI as an outcome are examined. As shown in Table 10, in Subclass 3 which consists of medium-size firms, treatment effect is positive and statistically significant in 5% level, but not in other subclasses. Thus, positive effect on network diversity averaged throughout the period after 3.11 is indeed limitedly observed. DDD based on time-variant treatment variables, and obtained results are shown in Figure 8. Statistically significant treatment effects can be observed in Subclass 3, but they exposed after four years of 3.11 although point estimates are positive throughout the period. Thus, with these results, it can be difficult to assert direct causality between 3.11 and network diversity or concentration. Treatment variable in 2010 is not statistically significant in all subclasses. These results imply that there cannot be a convincing evidence of violation of parallel trend.

5.6 Discussion

From estimation results with DD, it is shown that the geographical diversification of the supply chain network has not been instigated toward the Nankai Trough Earthquake after 3.11, even though a firm had suppliers in hazardous regions of the Nankai Trough Earthquake before 3.11, regardless of firms' size, and the difference of geographical units to measure network diversity. This result can imply that only recognition of visible shock similar to future shock that firms may face cannot lead to the update of their unrelated trade diversity.

On the other hand, from estimation results with DDD it is shown that the cross-prefectural diversification of the supply chain network has been instigated toward the Nankai Trough Earthquake after 3.11 if a firm had suppliers in both hazardous regions of the Nankai Trough Earthquake before 3.11 and damaged regions of 3.11, but only in the group of medium-size firms. This result can imply that recognition of visible shock explicitly conditioned by direct shock on their incumbent suppliers matters on the update of their unrelated trade diversity for medium-size firms. This result may reflect some heterogeneity of disaster effect depending on firm size. That is, on the one hand, the effect of pre-disaster planning on the supply chain may be trivial for larger firms as their supply chains networks are already diversified but not so for smaller firms. On the other hand, it may be difficult for smaller firms to find alternative partners because of high search costs even though, having learned from other disasters, they want to pursue such pre-disaster planning. In sum, the update of unrelated trade diversity has progressed in only firms that are not bound by capacity constraint due to search and maintenance cost of alternative suppliers compared with smaller firms but are dependent on each supplier compared with larger firms.

6. Conclusion

In this study, we examined the impact of the change in risk perception after a disaster on the supply chain network by looking at pre-disaster preparation evaluated by the update of firms' unrelated trade diversity, which has been rarely touched on in previous studies. In the process of examination, I exploited the Great East Japan Earthquake as an instance of actual and visual disaster shock, and the Nankai Trough earthquake, the forthcoming mega earthquake in West Japan, as an example of future and similar disaster shock. The impact of risk perception on pre-disaster preparation on supply chain can be an interesting point to illustrate firms' behavior under the tradeoffs around network size, capacity constraints, and uncertainty.

This study contributes to the literature as follows. First, this study examined risk perception using a rigorous econometric approach based on a quasi-experiment, rather than anecdotal information. In empirical analysis, I utilized firm-level and long-term network data from before and after the Great East Japan Earthquake. Second, from the perspective of economic geography and international management, this study is one of few investigations which examines the determinant of unrelated variety of local industry. In particular, this study is all the more remarkable because it revealed causal effect of disaster shock on unrelated diversity, which should be strictly distinguished from the literature examining only association.

The results are summarized as follows. There could not be statistical evidence of the geographical diversification of the supply chain network toward the Nankai Trough Earthquake after 3.11, even though a firm had suppliers in hazardous regions of the Nankai Trough Earthquake before 3.11. This result can imply that only recognition of visible shock could not lead firms to the update of their unrelated trade diversity. However, I could observe the cross-prefectural diversification of the supply chain in the group of medium-sized firms that also had suppliers in the damaged regions of 3.11. In sum, the recognition of visible shock explicitly conditioned by direct shock on their incumbent suppliers can matter on the update of unrelated trade diversity, and it has progressed in only firms that were relatively not bound by capacity constraint due to search and maintenance cost but were still dependent on each supplier.

Here I describe the future work of this paper for further progress. First, the empirical analysis did not explicitly consider the interaction between firms that arises from the disaster preparation strategy. One aspect of risk perception and pre-disaster preparation in the supply chain network could be the requirement that all the firms in the supply chain participate in the preparation. In other words, one firm's preparation by itself might have no meaning unless considered as part of the whole chain. In this respect, the preparation behavior needs to be examined by explicitly considering the strategic interaction among the firms as well.

Second, this study attempts to estimate the treatment effect assuming that the treatment variable is binary. However, this assumption can be unrealistic because of the following circumstances. The effect of the disaster can be larger as the proportion of the suppliers located in the damaged or hazardous regions becomes larger. In addition, the disaster damage could be considered multilevel as some firms were damaged by both ground movement and the tsunami and others were damaged only by ground movement. Thus, explicit consideration of these concerns would be required using a matching method as in the generalized PSM (Imai and Van Dyk, 2004) applicable to multilevel treatment.

Finally, this study defines the treatment by the transaction relationships in 2008. However, this definition based on the information of a single period may be insufficient because there could be some firms that were supplied from the damaged or hazardous regions only in 2008. Thus, this contingency could be eliminated by controlling the temporal embeddedness of the transactional relationships between firms.

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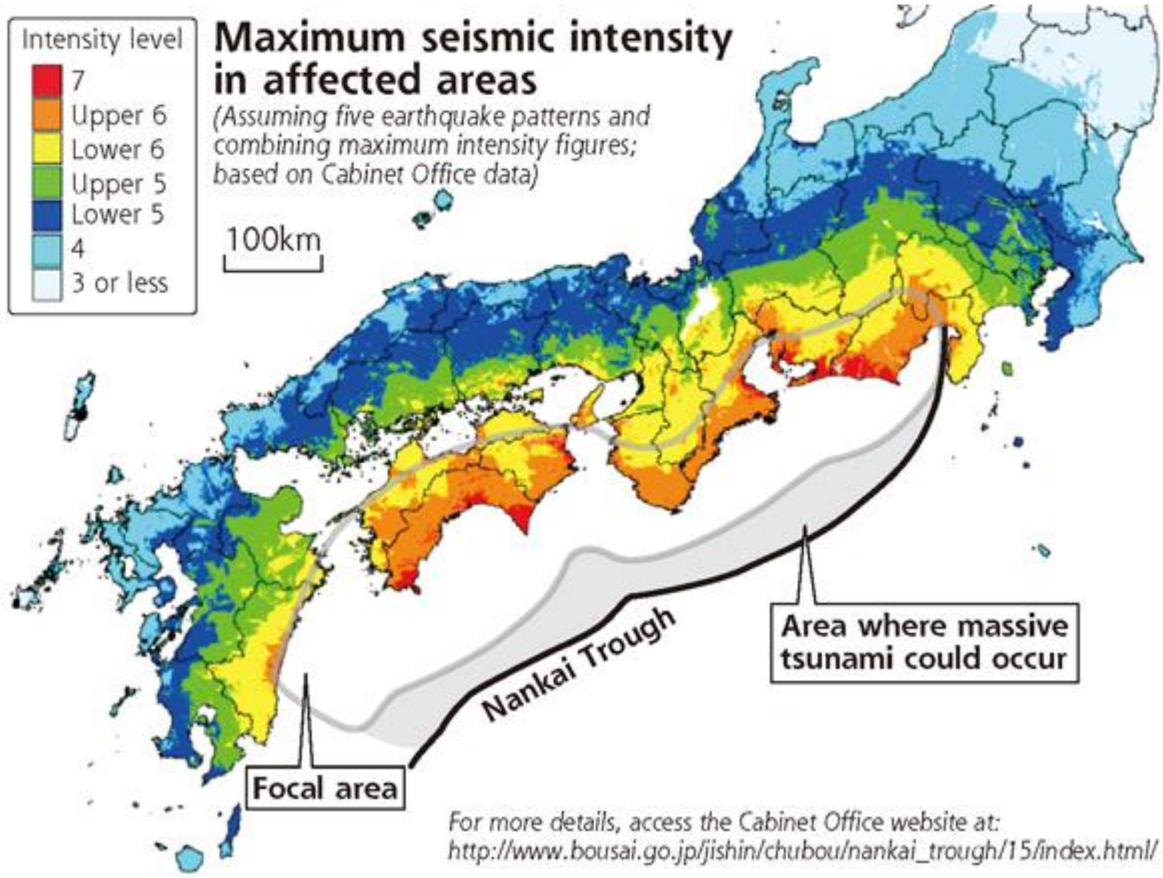

Figure 1. Estimated seismic intensity of the Nankai Trough Earthquake[12]

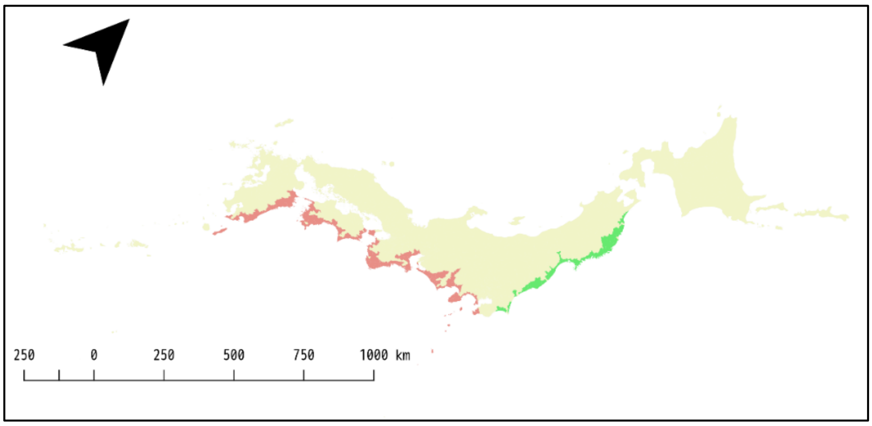

Figure 2. Tsunami damaged regions of the Great East Japan Earthquake (green) and tsunami hazardous regions of the Nankai Trough Earthquake (red)

[12] Harner, S. (2012). *BTW, Get Ready for a 34 Meter Tsunami*. Forbes. Available in https://www.forbes.com/sites/stephenharner/2012/04/02/btw-get-ready-for-a-34-meter-tsunami. Last accessed: October 7 2018.

Table 1: Estimation result of binomial logistic regression on all manufacturing samples corresponding to the existence of suppliers in hazardous regions of the Nankai Trough Earthquake (2008)

	beta	z-val	
(Intercept)	−3.112	−22.533	***
lnSALES	0.054	2.189	**
lnEMP	−0.570	−17.615	***
lnSALES×lnEMP	0.091	24.110	***
lnSALES×KOIKI_Chugoku	0.092	2.754	***
lnSALES×KOIKI_Hokkaido	−0.495	−3.842	***
lnSALES×KOIKI_Hokuriku	0.081	1.784	*
lnSALES×KOIKI_Kinki	0.115	5.277	***
lnSALES×KOIKI_Shikoku	−0.158	−1.988	**
lnSALES×KOIKI_Shuto	0.129	6.896	***
lnSALES×KOIKI_Tohoku	0.071	1.919	*
lnEMP×KOIKI_Hokkaido	0.444	2.825	***
lnEMP×KOIKI_Kyushu	0.114	3.452	***
lnEMP×KOIKI_Okinawa	−0.546	−2.400	**
lnEMP×KOIKI_Shikoku	0.211	2.231	**
2-digit dummy		YES	
Koiki dummy		YES	
PseudoR-sq		0.169	
n		92308	

Notes: Significant in ***1%, **5%, *10%

Table 2: Estimation result of binomial logistic regression on matched sample corresponding to the existence of suppliers in damaged regions the Great East Japan Earthquake (2008)

	beta	z-val	
(Intercept)	−8.175	−13.221	***
lnSALES	0.694	7.713	***
lnEMP	−0.571	−3.976	***
lnEMP^2	0.058	5.488	***
lnSALES×KOIKI_Shuto	−0.212	−1.902	*
lnEMP×KOIKI_Chubu	0.156	1.415	
lnEMP×KOIKI_Chugoku	0.352	1.885	*
lnEMP×KOIKI_Kinki	0.275	2.553	**
lnEMP×KOIKI_Shuto	0.231	1.665	*
lnSALES×KOIKI_Tohoku	−0.192	−2.203	**
2-digit dummy		YES	
Koiki dummy		YES	
PseudoR-sq		0.298	
n		17734	

Notes: Significant in ***1%, **5%, *10%

Table 3: Chi-square overall test corresponding to the existence of suppliers in hazardous regions of the Nankai Trough Earthquake (2008)

	Subclass 1	Subclass 2	Subclass 3	Subclass 4	Subclass 5
# of Treatment (NT=1)	6101	1163	601	385	338
# of Control (NT=0)	7235	904	378	161	61
Overall Balance (H0: Balanced)	p<0.01	p<0.1	n.s.	n.s.	n.s.

Table 4: Chi-square overall test corresponding to the existence of suppliers in damaged regions the Great East Japan Earthquake (2008)

	Subclass 1	Subclass 2	Subclass 3	Subclass 4	Subclass 5
# of Treatment (EJ=1)	210	210	211	209	209
# of Control (EJ=0)	13126	1857	768	337	190
Overall Balance (H0: Balanced)	p<0.01	p<0.1	n.s	n.s.	n.s.

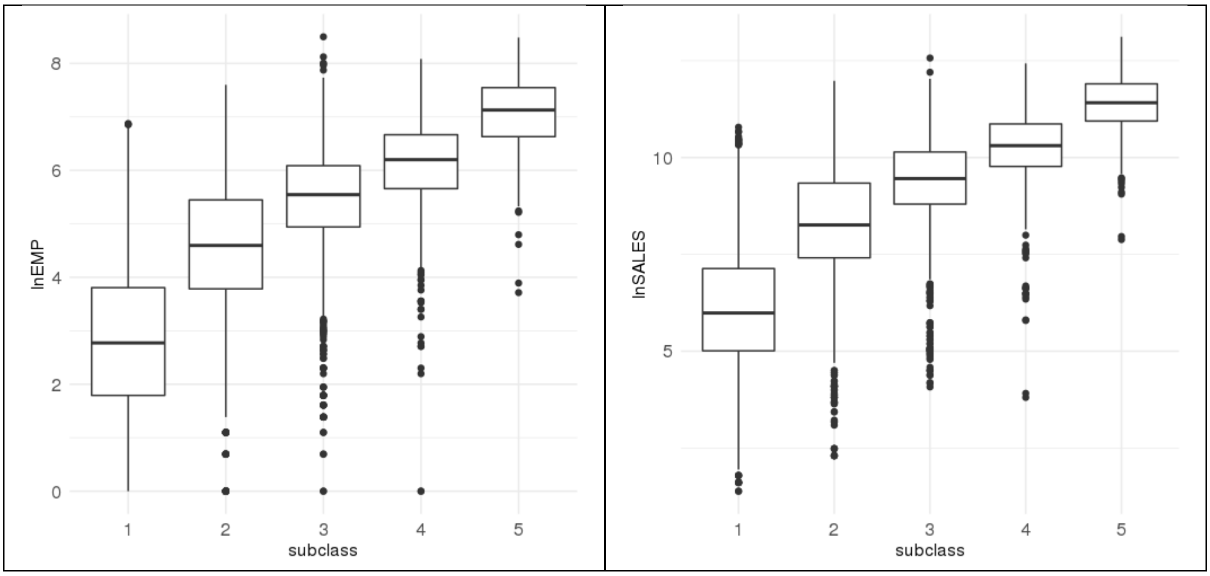

Figure 3. Box plots of logged number of employees [persons] (Left) and logged sales [millon ¥] (Right) in each subclass (2008)

Table 5: Average number of employees and average sales (inverse log transformed, 2008)

	Subclass 1 (Micro)	Subclass 2 (SME)	Subclass 3 (Medium-size)	Subclass 4 (Large)	Subclass 5 (Leading)
# of employees [persons]	17.2	92.7	219.9	435.8	1136.5
Sales [million ¥]	449.7	3780.3	10804.9	26566.8	85528.1

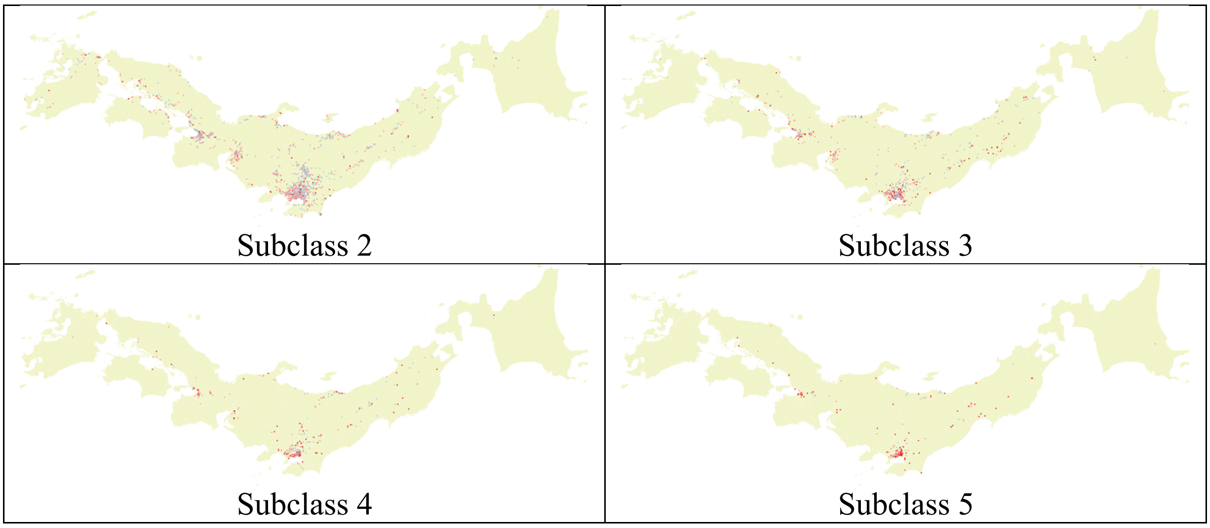

Figure 4. Spatial distribution of the firms in each subclass in 2008
(Red: NT=1&EJ=1, Pink: NT=1&EJ=0, Blue: NT=0)

Table 6: Observed number of firms in each treatment status (2008)

	Subclass 1	Subclass 2	Subclass 3	Subclass 4	Subclass 5
NT=0&EJ=0	7141	822	313	118	35
NT=1&EJ=0	5985	1035	455	219	155
NT=0&EJ=1	94	82	65	43	26
NT=1&EJ=1	116	128	146	166	183

Table 7: Estimation results of DD for examining H1 with time-invariant treatment variable
(Dependent variable: Prefecture level 1/HHI, 2009-2017)

	Subclass 2		Subclass 3		Subclass 4		Subclass 5		
	beta	t-val	beta	t-val	beta	t-val	beta	t-val	
NT×After	−0.020	−0.653	0.009	0.174	0.028	0.397	0.17	1.712	*
Firm FE	YES		YES		YES		YES		
Year FE	YES		YES		YES		YES		
2-digit FE	YES		YES		YES		YES		
Koiki FE	YES		YES		YES		YES		
2-digit×Year FE	YES		YES		YES		YES		
Koiki×Year FE	YES		YES		YES		YES		
n	18603		8811		4914		3591		

Notes: Significant in ***1%, **5%, *10%. Standard errors are clustered at the firm level.

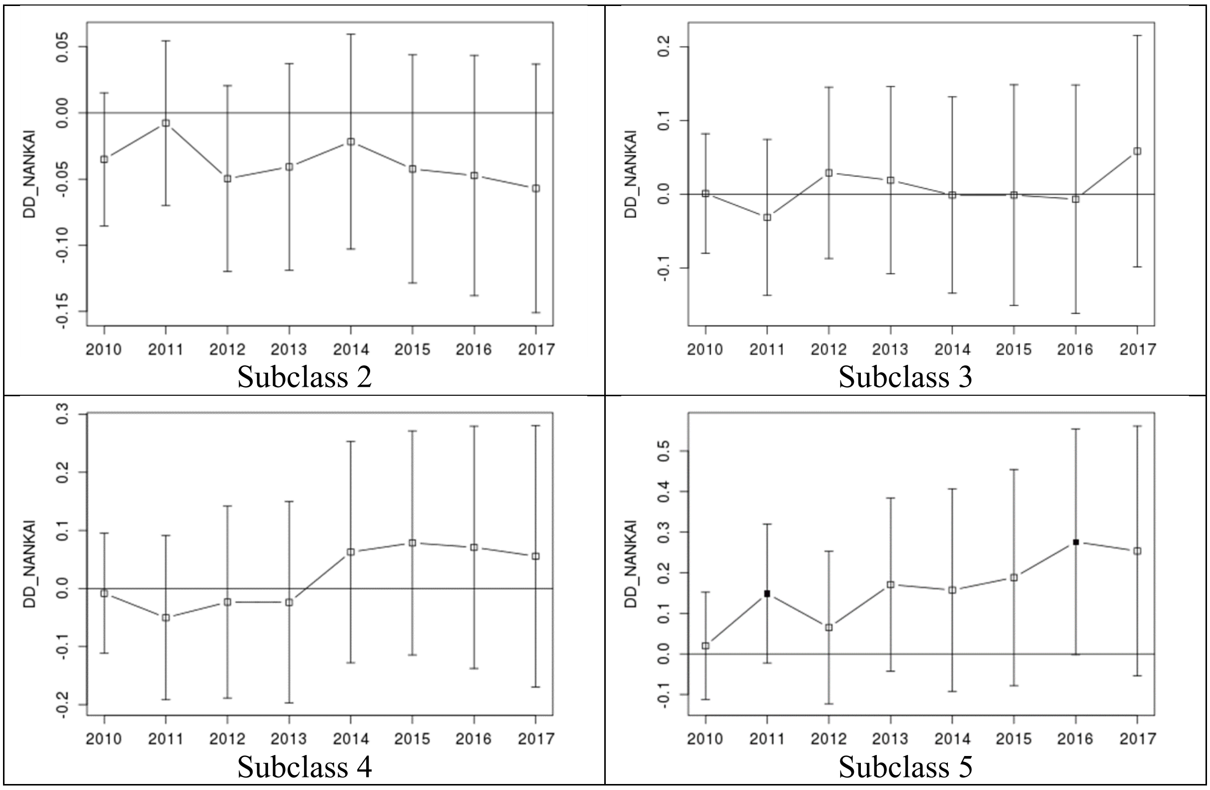

Figure 5. Estimation results of DD with time-variant treatment variables
(Dependent variable: prefecture level 1/HHI, 2009-2017)

Notes: Standard errors are clustered at the firm level. A plot represented with "■" means that treatment variable corresponding to the year is statistically significant at least 10% level. Vertical bars added on plots represent 95% confidence interval.

Table 8: Estimation results of DD with time-invariant treatment variable
(Dependent variable: Koiki region level 1/HHI, 2009-2017)

	Subclass 2			Subclass 3		Subclass 4		Subclass 5		
	beta	t-val		beta	t-val	beta	t-val	beta	t-val	
NT×After	−0.029	−1.993	**	−0.023	−1.105	−0.017	−0.619	0.07	1.905	*
Firm FE	YES			YES		YES		YES		
Year FE	YES			YES		YES		YES		
2-digit FE	YES			YES		YES		YES		
Koiki FE	YES			YES		YES		YES		
2-digit×Year FE	YES			YES		YES		YES		
Koiki×Year FE	YES			YES		YES		YES		
n	18603			8811		4914		3591		

Notes: Significant in ***1%, **5%, *10%. Standard errors are clustered at the firm level.

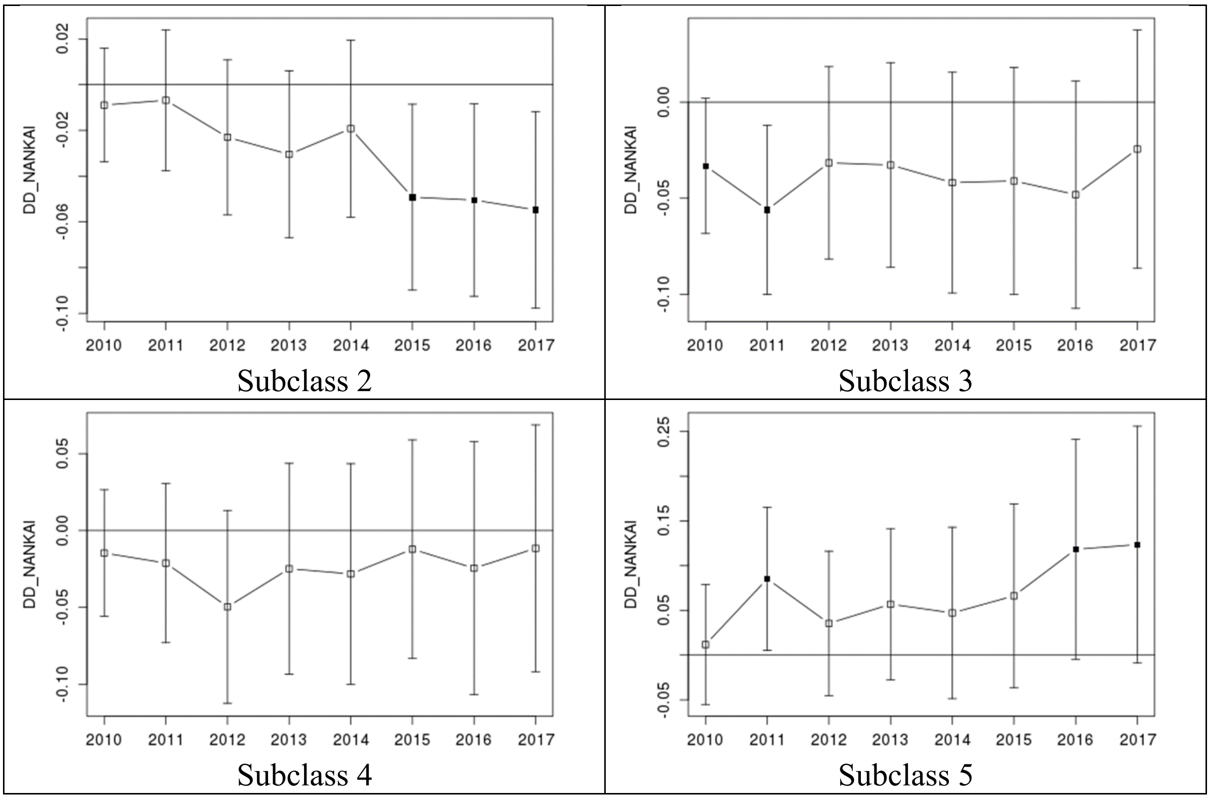

Figure 6. Estimation results of DD with time-variant treatment variables
(Dependent variable: Koiki region level 1/HHI, 2009-2017)

Notes: Standard errors are clustered at the firm level. A plot represented with "■" means that treatment variable corresponding to the year is statistically significant at least 10% level. Vertical bars added on plots represent 95% confidence interval.

Table 9: Estimation results of DDD with time-invariant treatment variable
(Dependent variable: prefecture level 1/HHI, 2009-2017)

	Subclass 2		Subclass 3			Subclass 4		Subclass 5	
	beta	t-val	beta	t-val		beta	t-val	beta	t-val
NT×EJ×After	0.085	0.691	0.258	2.155	**	−0.031	−0.196	0.198	1.050
Firm FE	YES		YES			YES		YES	
Year FE	YES		YES			YES		YES	
2-digit FE	YES		YES			YES		YES	
Koiki FE	YES		YES			YES		YES	
2-digit×Year FE	YES		YES			YES		YES	
Koiki×Year FE	YES		YES			YES		YES	
n	18603		8811			4914		3591	

Notes: Significant in ***1%, **5%, *10%. Standard errors are clustered at the firm level.

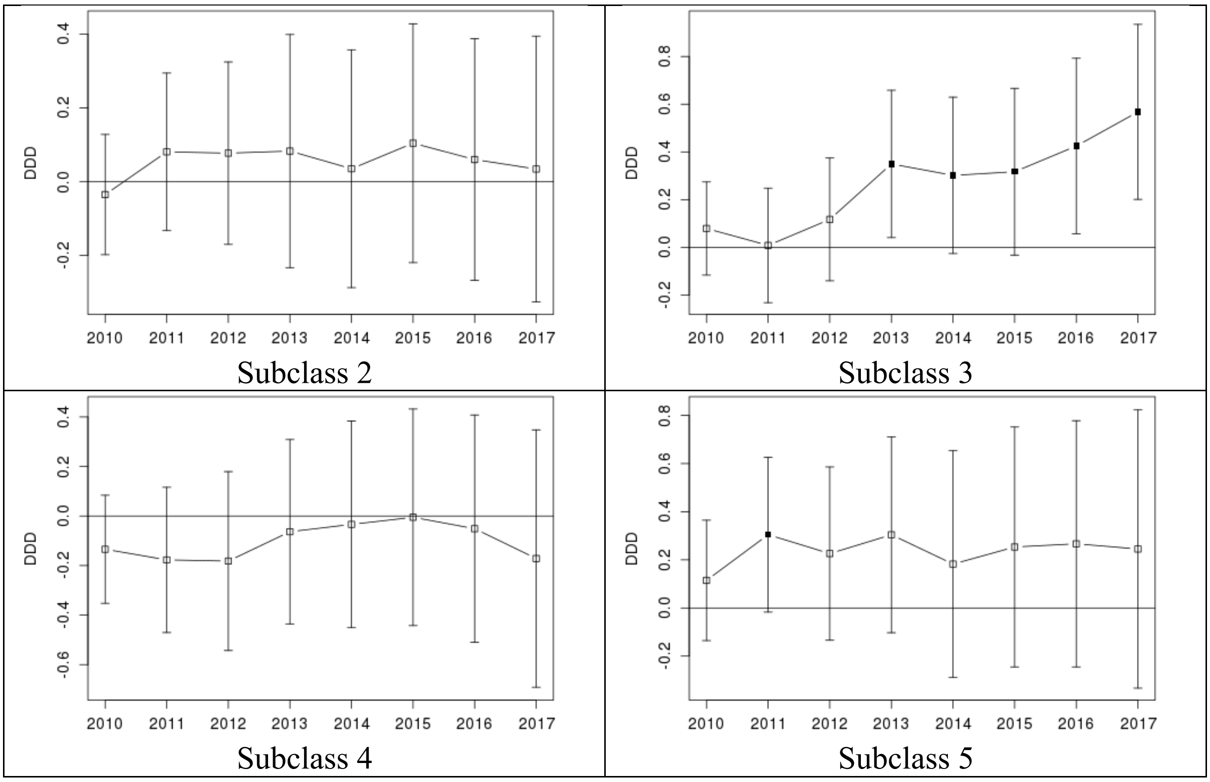

Figure 7. Estimation results of DDD with time-variant treatment variables
(Dependent variable: prefecture level 1/HHI, 2009-2017)

Notes: Standard errors are clustered at the firm level. A plot represented with "■" means that treatment variable corresponding to the year is statistically significant at least 10% level. Vertical bars added on plots represent 95% confidence interval.

Table 10: Estimation results of DDD with time-invariant treatment variable
(Dependent variable: Koiki region level 1/HHI, 2009-2017)

	Subclass 2		Subclass 3			Subclass 4		Subclass 5	
	beta	t-val	beta	t-val		beta	t-val	beta	t-val
NT×EJ×After	0.007	0.151	0.105	2.169	**	0.020	0.370	−0.051	−0.780
Firm FE	YES		YES			YES		YES	
Year FE	YES		YES			YES		YES	
2-digit FE	YES		YES			YES		YES	
Koiki FE	YES		YES			YES		YES	
2-digit×Year FE	YES		YES			YES		YES	
Koiki×Year FE	YES		YES			YES		YES	
n	18603		8811			4914		3591	

Notes: Significant in ***1%, **5%, *10%. Standard errors are clustered at the firm level.

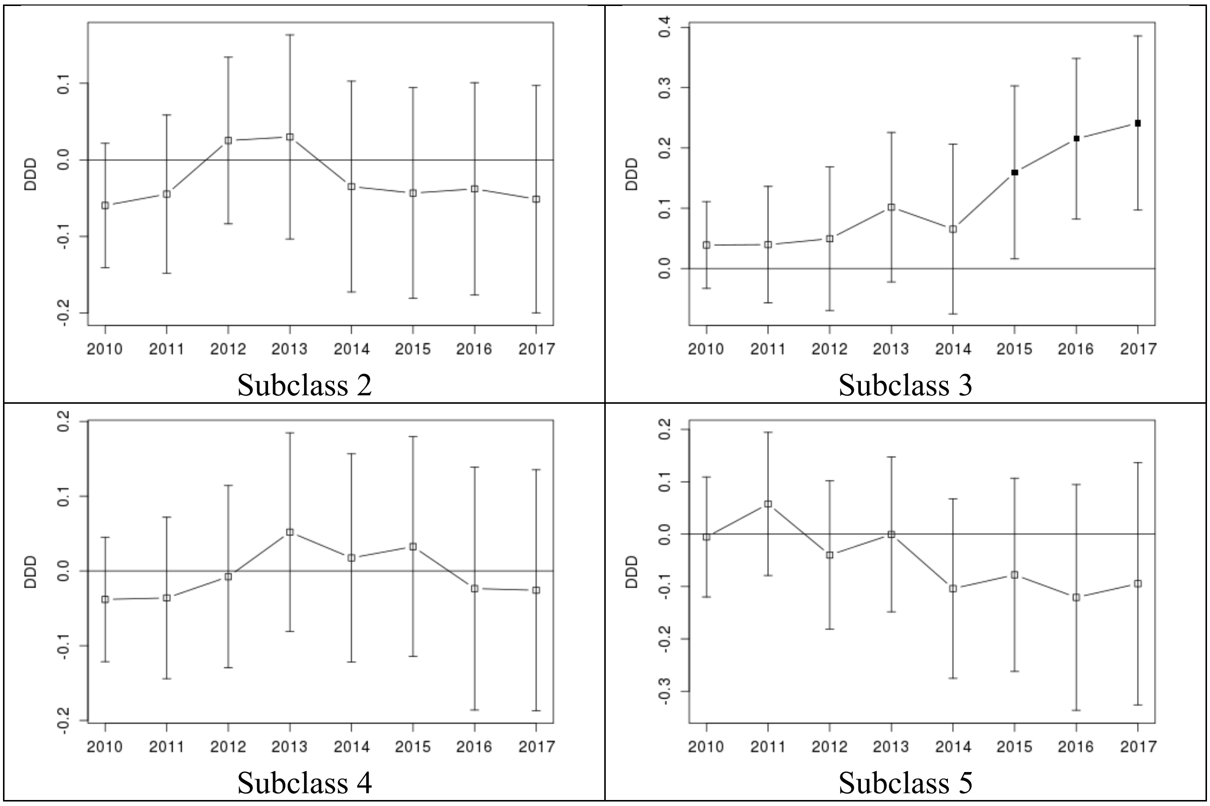

Figure 8. Estimation results of DDD with time-variant treatment variables
(Dependent variable: Koiki region level 1/HHI, 2009-2017)

Notes: Standard errors are clustered at the firm level. A plot represented with "■" means that treatment variable corresponding to the year is statistically significant at least 10% level. Vertical bars added on plots represent 95% confidence interval.