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# HOW DO SUPPLY CHAIN NETWORKS AFFECT THE RESILIENCE OF FIRMS TO NATURAL DISASTERS? EVIDENCE FROM THE GREAT EAST JAPAN EARTHQUAKE*

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**ABSTRACT.** This paper uses firm-level data to examine how supply chain networks affected the recovery of firms from the Great East Japan Earthquake. Extensive supply chains can negatively affect recovery through higher vulnerability to network disruption and positively through support from trading partners, easier search for new partners, and general benefits of agglomeration. Our results indicate that networks with firms outside of the impacted area contributed to the earlier resumption of production, whereas networks within the region contributed to sales recovery in the medium term. The results suggest that the positive effects of supply chains typically exceed the negative effects.

## 1. INTRODUCTION

Dynamic economic resilience to natural disasters, defined as speedy recovery through the repair and reconstruction of capital stock (Rose, 2007), is influenced by many factors in the economy. One possible factor in this resilience is the structure of supply chain networks, that is, networks between the producers of materials, parts, and components and their final assemblers, as argued by Henriet, Hallegatte, and Tabourier (2011). The simulation analysis of Henriet et al. (2011) uses a model based on input–output (IO) tables and implies that the expansion of interregional supply chain networks leads to weaker

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resilience because the negative impacts of disasters can propagate across regions through supply chain disruption. Their argument appears to be consistent with the experience of Japan, a country with supply chain networks that expand across regions (Fujiwara and Aoyama, 2010), in the aftermath of the Great East Japan Earthquake[1] (hereafter, the earthquake) in 2011. For example, Toyota and Honda had to stop or reduce production in the plants unaffected by the earthquake, including those in the United States because the supply of parts and components from the impacted area was disrupted (*Nikkei* (the Japanese version), May 3, 2011). Tokui et al. (2012), using a numerical simulation based on an IO model similar to Henriet et al. (2011), estimated that 90 percent of the output loss in Japan due to the earthquake resulted from indirect effects through the disruption of supply chains rather than the direct effects of damage caused by the disaster.

Thus, both anecdotal evidence and the results from IO models suggest that supply chain networks expanding across regions reduce economic resilience to natural disasters. However, rigorous econometric evidence on this issue is still missing. Some studies such as Dahlhamer and Tierney (1998), Webb, Tierney, and Dahlhamer (2002), and Altay and Ramirez (2010) examined the determinants of business recovery from natural disasters using firm-level data, but these studies did not incorporate the structure of supply chain networks as a potential determinant.[2] In a different strand of disaster recovery literature, Nakagawa and Shaw (2004) and Aldrich (2011, 2012) empirically showed that social networks in local communities, approximated by, for example, the level of community activities, promote recovery of the regional population after natural disasters. Cho et al. (2001) modeled negative impacts of earthquakes on metropolitan economies through transportation networks. However, supply chain networks are not the focus of these studies. Therefore, whether and how supply chain networks affect economic resilience to natural disasters is still unclear and remains an empirical question. This paper attempts to examine this issue for the first time, using firm-level data from the impacted areas of the Great East Japan Earthquake.

Our analysis is based on two datasets, one from a survey of firms in the impacted area conducted after the earthquake and the other from another survey conducted a few years before the earthquake to collect detailed information about the suppliers and clients of each firm. The latter dataset is unique in that it contains information on most of the supply–client relationships in the entire country. We estimated the impact of the number of suppliers and clients of firms inside and outside of the impacted area on two recovery measures: the recovery time after the earthquake, that is, the length of time before resuming operations, and the sales growth from the pre- to postearthquake period.

Despite the anecdotal evidence and simulation analysis discussed above, supply chain networks are not always harmful to disaster recovery. After the earthquake, impacted firms often benefited from physical, psychological, and financial support from suppliers and clients during the process of recovery. Additionally, it is often observed that the firms that lost supply or demand from damaged firms were able to find new partners by utilizing information obtained through supply chain networks. Moreover, supply chain networks within the region provide the standard benefits from agglomeration through information spillovers and input sharing even after disasters.

[1]The Great East Japan Earthquake is the fourth largest earthquake in terms of magnitude recorded in world history (U.S. Geological Survey, 2013), killing more than 18,000 people (including those missing).

[2]Although Altay and Ramirez (2010) argued that they incorporated supply chains into their analysis, they simply classified firms in the manufacturing sector as upstream firms (i.e., suppliers) and those in the retail sector as downstream firms (clients). Therefore, supply chain networks within the manufacturing sector remain unexamined.

From our econometric analysis using firm-level data, we find that having more suppliers and clients outside of the impacted area shortened the recovery time but had only weak effects on sales growth in the medium term, that is, in the half-year period after the earthquake. In contrast, having more suppliers and clients in the impacted area did not affect the recovery time but did improve medium-run sales growth. In addition, we identify a negative effect from supply chains on recovery through the disruption of supply and demand and two positive effects through support and substitution. Our findings suggest that the positive effects from supply chain networks typically outweigh the negative effects, leading to a net positive effect.

This study contributes to several strands of literature as follows. First, and most importantly, these findings elucidate the positive effect of supply chain networks across regions on economic resilience to natural disasters, although the academic literature and public argument have focused more on their negative propagation effects. In addition, we find that supply chains outside the region are more helpful in short-term recovery, whereas those within the region help with medium-term recovery, suggesting that diversified networks are beneficial to resilience. These conclusions provide important implications for firms and policy makers in terms of addressing the risks of natural disasters.

Second, the results of this study may be useful to the research measuring output losses due to natural disasters using the simulation of theoretical models, such as IO and computable general equilibrium (CGE) models (Rose et al., 1997; Rose and Liao, 2005; Hallegatte and Przyluski, 2010). Hallegatte (2012) found that output losses are amplified by supply chain relationships, particularly when substitution between inputs is more difficult. Because this study's finding implies that firms often substitute damaged suppliers and clients with new partners, output losses from natural disasters are likely to be smaller than those predicted by these simulations. Therefore, this study suggests that theoretical models and simulation analysis in this field be enriched by incorporating larger substitution effects.

Third, this study provides an interesting case from the viewpoint of network science. The statistical modeling of network dynamics has recently gained significant attention (Snijders and Doreian, 2010, 2012), but network evolution through the substitution of exogenously terminated ties has not yet been deeply explored.

Fourth, the results of this study can also contribute to the literature on the long-term economic impacts of natural disasters, which has yielded mixed findings. Skidmore and Toya (2002) found no negative effect from natural disasters on long-term growth, whereas Cavallo et al. (2013), duPont IV and Noy (2012), and Noy and Nualsri (2007) found a persistent negative effect. Xiao (2011) found a negligible effect from a flood in the United States on income in the long term but a long-lasting negative effect on agricultural output. In closely related literature, Davis and Weinstein (2002, 2008) did not find a significant effect of man-made disasters, such as wartime bombing, on long-term economic trends. These mixed results suggest that the effects of natural and man-made disasters on economic activities vary depending on the conditions and characteristics of the economy. Our results demonstrate that the structure of supply chain networks is one of these conditions.

Finally, this study contributes to the literature on economic geography by identifying the benefits and costs of economic agglomeration. Since Marshall (1890), it has been believed that the agglomeration of firms and workers improves firm productivity and reduces production costs through input sharing, knowledge spillovers, and labor pooling (Bhat, Paleti, and Singh, 2014; Jofre-Monseny, Marín-López, and Viladecans-Marsal, 2013; Duranton and Puga, 2004). Recently, Chen and Wu (2013) find that industrial agglomeration benefits employees through a higher level of employer compliance to pension contribution in China. Our finding that supply chain networks within the region promote medium-term recovery from natural disasters suggests that the positive effects of agglomeration function effectively even in the aftermath of disasters. However, this study also points to a new source for the costs of agglomeration, as it finds that the physical proximity of transaction partners has a negative effect on short-term recovery from region-specific shocks through the disruption of local supply chain networks.

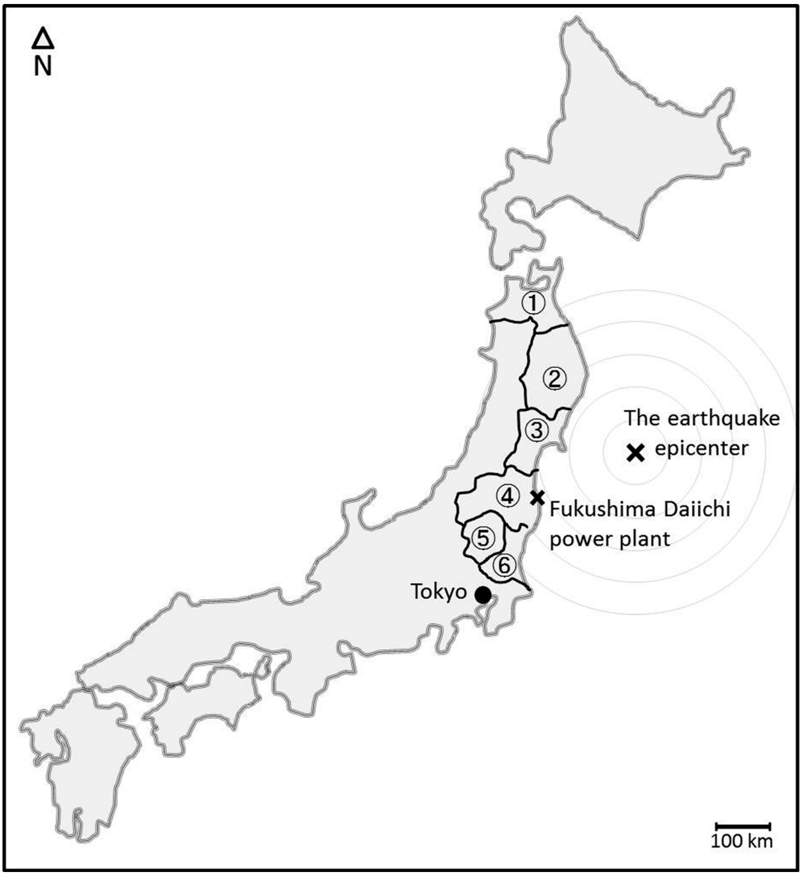
The rest of the paper is organized as follows. In the next section, we describe the dataset used in this study. Section 3 explains conceptual frameworks and estimation methods, and Section 4 shows estimation results. Section 5 concludes.

## 2. DATA

### *Description of the Data Sources*

The dataset used in this study is based on two data sources. The first data source is data from a plant-level survey conducted by the Research Institute of Economy, Trade and Industry (hereinafter, the RIETI survey) in January and February in 2012, 10 months after the Great East Japan Earthquake and subsequent tsunami on March 11, 2011, of plants in areas impacted by the earthquake. The implementation of the survey was subcontracted to Teikoku Databank, one of the largest corporate research companies in Japan, which already had information on most of the plants in the impacted area prior to the earthquake. The area impacted by the earthquake is formally defined by the Law on Special Great East Japan Earthquake Reconstruction Areas and include cities, towns, and villages in the prefectures of Aomori, Iwate, Miyagi, Fukushima, Tochigi, and Ibaraki. Figure 1 shows the epicenter of the earthquake and the impacted prefectures. The survey targeted all 6,033 plants (with some exceptions, as explained below) that were in the manufacturing sector, were located in the impacted area, and had at least five employees before the earthquake, according to the prior information possessed by Teikoku Databank. Two categories of plants whose recovery was impeded largely by government regulations were excluded from the survey because one of the primary objectives of the survey was to determine how firm characteristics affected recovery from the earthquake. The first category of excluded plants was those in the seafood processing industries. In some cases, seafood processing firms were not allowed to reconstruct their plants, which are often located near fishery ports, due to regulations by local governments for integrated regional development plans for recovery (Ministry of Agriculture, 2012). Therefore, reconstruction of these firms' plants after the disaster was prevented by regulation, even if their recovery would otherwise have been possible. In fact, according to the Small and Medium Enterprise Agency of Japan (2012), only 50 percent of the firms in the seafood processing industry in the impacted area had restarted production by January 2012, whereas 67 percent of firms in other industries had done so by then. The other category of excluded plants were those located within a 20-km radius of the Fukushima Daiichi Nuclear Power Plant because they were required by the government to evacuate the area due to possible releases of radioactivity from the power plant at the time of the survey.

A questionnaire on the level of damage suffered as a result of the earthquake and business activities before and after the earthquake was sent by mail in January 2012, and plants were requested to send back their responses by February 2012. For the plants that did not respond, telephone calls were made to encourage responses. A total of 2,117 effective responses were received, that is, the response rate was 35 percent, which is high for this type of plant-level survey. Plants that were located in the impacted area before the earthquake but relocated or closed their business after the earthquake were also of interest in the survey, as long as the Teikoku Databank could capture their current contact address. Among the 2,117 plants, 15 had relocated or were going to relocate, six




*Note*: The labeled prefectures are (1) Aomori, (2) Iwate, (3) Miyagi, (4) Fukushima, (5) Tochigi, (6) Ibaraki.

FIGURE 1: Earthquake Epicenter and Impacted Prefectures.

had closed or were going to close their business, and three had merged with other firms. The inclusion of relocated and closed plants in the sample is unique and valuable for a survey intended to examine whether and how well firms recover from disasters.

The other data source is data from Tokyo Shoko Research (the TSR data), another large corporate research company in Japan. The TSR data contain corporate information, such as a firm's location, sales, and number of employees, and information on up to 24 suppliers of intermediates and up to 24 clients of products for each firm. The information on suppliers and clients can be merged with the corporate information data to establish the characteristics of each supplier and client. Although the upper limit of the number of suppliers and clients, 24, is clearly too small for many large firms, it still allows most of the supply chain networks to be captured by looking at the supplier–client relations from both directions. RIETI purchased the entire dataset, which includes corporate information for 803,705 firms and transaction information for 3,904,380 supplier–client pairs, from TSR in 2006. The corporate information was collected in 2005 for 67 percent of the firms in the TSR data, in 2004 for 28 percent of the firms, and in 2002, 2003, or 2006 for the other 5 percent. The maximum number of suppliers for one firm was 7,474, and the maximum

TABLE 1: Damage Caused by the Great East Japan Earthquake

| | Raw Data from the Impacted Area | | Data after Matching with the TSR Data | |
|---|---|---|---|---|
| | Number of Firms | Share of Total (%) | Number of Firms | Share of Total (%) |
| No damage | 519 | 26.0 | 227 | 25.2 |
| Partial damage | 1,217 | 60.9 | 553 | 61.3 |
| Half destruction | 147 | 7.36 | 72 | 7.98 |
| Complete destruction | 114 | 5.71 | 50 | 5.54 |
| Total | 1,997 | 100 | 902 | 100 |

number of clients was 7,139. These large numbers support our previous argument that the TSR data cover most of the supply chain networks in Japan.

It should be noted that because the TSR dataset is at the firm level, supplier–client relationships at the plant level could not be identified. This data limitation leads to the following problem. When a particular firm has plants both inside and outside the impacted area, the TSR data can show the total number of suppliers and clients for the firm, but we cannot identify the number of suppliers or clients for a plant in the impacted area. Therefore, when we merge the RIETI data at the plant level with the TSR data, we dropped the plants in the impacted area with headquarters outside the area from our sample. This procedure allows us to focus on smaller single-plant firms in the impacted area, and we will hereafter use the terms "firm" and "plant" interchangeably. However, because plants with headquarters outside the impacted area constitute only 7.3 percent of all plants in the RIETI data, this procedure may not substantially bias the results. In addition, when a firm in the impacted area supplies its products to a plant inside the area but with a headquarter outside the area, the TSR data mistakenly indicate that the supplier has a client outside the area. We later distinguish between the effects of suppliers (clients) inside and outside the impacted area, but due to this misspecification, the effect of suppliers (clients) in the impacted area may be underestimated, whereas the effect of suppliers (clients) outside the area may be overestimated.

We merged the RIETI and TSR data using the names and addresses of the firms. In the merging process, we had to exclude the firms whose information was in the RIETI data but not in the TSR data in addition to the firms with headquarters outside the impacted area as explained above. One reason for this mismatch between the two data sources is that although both Teikoku Databank and TSR have information on most firms in Japan, their coverage is different, particularly for small and microenterprises, depending on their ability to locate firms and interview them. Another reason for this mismatch is that the TSR data were collected before 2006, whereas the RIETI data were collected in 2012. Therefore, firms that started or closed their business or were renamed between 2006 and 2012 were excluded. After excluding firms with obvious errors in their data, we had a total of 902 firms in the sample used for our analysis.

*Descriptive Statistics*

Most of the firms in the RIETI data were affected by the earthquake and subsequent tsunami. Among the approximately 2,000 firms that were in the sample prior to merging with the TSR data, 114 firms, or 5.7 percent, reported that their equipment was completely or almost completely destroyed, and hence that they had to stop operations (Table 1). Another 147 firms, or 7.4 percent, reported that they had to stop part of their operations because about half of their equipment was destroyed, whereas 1,217 firms, or 61 percent, reported partial damage from the earthquake or the tsunami. Finally, 519 firms, or 26 percent, reported no damage from the disaster. After merging these data with the TSR data, we found a similar distribution of firms, in terms of the level of damage, in the sample used in our analysis (right columns of Table 1).

According to the Small and Medium Enterprise Agency of Japan (2011), 26 percent of member firms of the chambers of commerce and industry in some of the impacted prefectures (Aomori, Iwate, Miyagi, and Fukushima Prefectures) were completely destroyed by the disaster, whereas 7 percent were "half-damaged." The proportion of completely damaged firms in our sample is lower than the corresponding proportion in the SME Agency (2011) information, most likely for the following two reasons. First, following the official definition of the impacted area, the RIETI survey targeted Ibaraki and Tochigi Prefectures in addition to Aomori, Iwate, Miyagi, and Fukushima Prefectures, which were targeted by the SME Agency's survey. In the former two prefectures, the damage caused by the disaster was relatively smaller (although still large in absolute terms) than in the latter four. Second, we excluded firms in the seafood processing industry and those near the Fukushima Daiichi Nuclear Power Plant, where damage was substantial, as explained above.

The distribution of firms in our sample by prefecture and industry is shown in Table 2. The number of firms in each prefecture is similar, except for the number in Aomori, which includes only 26 firms. The industries of the firms vary; 32.5 percent are in light industry, such as the food industry and lumber and wood products industries, whereas 39.3 percent are in the metal and machinery industries. According to the *Kogyo Tokei Chosa* (Census of Manufacturers) conducted by the Ministry of Economy, Trade and Industry in 2010, 39 and 40 percent of plants in the six prefectures were in the light industry and the metal and machinery industries, respectively. Therefore, the industry distribution in our sample is similar to that of the population in the impacted area.

Table 3 presents summary statistics for the key variables. The average and median numbers of workers in September 2010, before the earthquake, were 53.1 and 28.5, respectively. The average and median nominal sales in the half year from April to September 2010 were 1.17 and 0.14 billion yen, respectively. The average annual rate of change of sales from 2005 to 2010 was −5.4 percent. These figures indicate that the sample firms are mostly small and medium enterprises and that, on average, their business was declining before the earthquake.

In our estimation later, we will use two measures of recovery from the earthquake. The first is the number of days before resuming production after the earthquake, or the recovery time. The average and median recovery times were 14.9 and 5, respectively, and it was zero for approximately 30 percent of firms, meaning that those firms did not shut down their production. The maximum number of days was 330, the approximate number of days between the earthquake (March 2011) and survey (February 2012), meaning that those firms had not resumed production at the time of the survey. Thus, although some firms had difficulty reopening, many firms in our sample resumed their operations relatively soon after the earthquake. Therefore, we consider the recovery time to be a measure of short-term recovery. More precisely, it is an inverse measure of short-term recovery; a negative effect on the recovery time implies a positive effect on recovery.

The second measure of recovery is the change rate of sales from the second and third quarters (i.e., from April to September) of 2010 to the corresponding quarters in 2011. Because this change rate in sales contains sales six months after the earthquake, it is a measure of recovery in the medium term, or over a half-year postdisaster period. The average and median of this change rate of sales were 1.19 and −0.57 percent, respectively.

TABLE 2: Sample Firms by Prefecture and Industry

| Prefecture | Number of firms | Percent |
|---|---|---|
| Aomori | 26 | 2.9 |
| Iwate | 167 | 18.5 |
| Miyagi | 173 | 19.2 |
| Fukushima | 186 | 20.6 |
| Tochigi | 126 | 14.0 |
| Ibaraki | 224 | 24.8 |
| Total | 902 | 100 |
| Industry | | |
| Food | 115 | 12.8 |
| Beverages, tobacco, and feed | 27 | 3.0 |
| Textile mill products | 13 | 1.4 |
| Lumber and wood products, except furniture | 55 | 6.1 |
| Furniture and fixtures | 4 | 0.4 |
| Pulp, paper, and paper products | 16 | 1.8 |
| Printing and allied industries | 63 | 7.0 |
| Chemical and allied products | 14 | 1.6 |
| Petroleum and coal products | 2 | 0.2 |
| Plastic products, except as otherwise classified | 51 | 5.7 |
| Rubber products | 4 | 0.4 |
| Leather tanning, leather products, and fur skins | 1 | 0.1 |
| Ceramic, stone, and clay products | 90 | 10.0 |
| Iron and steel | 14 | 1.6 |
| Nonferrous metals and products | 18 | 2.0 |
| Fabricated metal products | 114 | 12.6 |
| General-purpose machinery | 6 | 0.8 |
| Production machinery | 52 | 5.8 |
| Business-oriented machinery | 22 | 2.4 |
| Electronic parts, devices, and electronic circuits | 13 | 1.4 |
| Electrical machinery, equipment, and supplies | 68 | 7.5 |
| Information and communication electronics equipment | 10 | 1.1 |
| Transportation equipment | 37 | 4.1 |
| Miscellaneous manufacturing | 76 | 8.4 |
| Nonmanufacturing | 17 | 1.9 |
| Total | 902 | 100 |

*Note:* Industry classifications are based on the Japan Standard Industrial Classification (Rev. 12): http://www.stat.go.jp/english/index/seido/sangyo/san07-3a.htm#e.

The lower rows of Table 3 indicate characteristics of the supply chain networks of the sample firms. Using the entire sample of the TSR data (i.e., including firms in the impacted area as well as those outside the impacted area), we computed the number of suppliers and clients inside and outside the impacted area for each firm. The average number of suppliers inside and outside the impacted area was 3.14 and 2.61, respectively, and their maximum was 104 and 24, respectively. These figures suggest that the sample firms had a relatively small number of suppliers and clients. However, as we mentioned in Section 2, the location of suppliers and clients may be misspecified if these suppliers and clients have plants both inside and outside the area. Therefore, the number of suppliers and clients inside the impacted area may be undervalued, whereas the number of those outside it may be overvalued.

TABLE 3: Summary Statistics of the Key Variables

| | $N$ | Mean | Median | S.D. | Min. | Max. |
|---|---|---|---|---|---|---|
| Number of workers (September 2010) | 902 | 53.12 | 28.50 | 84.23 | 4 | 1,120 |
| Number of workers (September 2011) | 899 | 53.14 | 29.00 | 85.64 | 0 | 1,086 |
| Rate of change of the number of workers (%, September 2010–2011) | 902 | −1.06 | 0.00 | 14.05 | −100 | 118 |
| Rate of change of the number of full-time workers (%, 2005–2010, annual) | 902 | 1.52 | 1.23 | 10.60 | −66 | 61 |
| Sales (April–September, 2010, billions of yen) | 902 | 1.17 | 0.14 | 20.01 | 0 | 600 |
| Sales (April–September, 2011, billions of yen) | 883 | 1.22 | 0.14 | 21.90 | 0 | 650 |
| Rate of change of sales (%, April–September 2010 to April–September 2011) | 883 | 1.19 | −0.57 | 39.34 | −100 | 284 |
| Rate of change of sales (%, 2005–2010, annual log growth rate) | 902 | −5.40 | −2.52 | 22.80 | −185 | 174 |
| Number of days before resuming operation | 902 | 14.86 | 5 | 41.81 | 0 | 330 |
| Number of days when supplies were disrupted | 828 | 21.03 | 7 | 46.58 | 0 | 330 |
| Number of suppliers | | | | | | |
| In the impacted area | 902 | 3.14 | 2 | 5.22 | 0 | 104 |
| – in log form (after adding 1) | 902 | 1.10 | 1.10 | 0.75 | 0 | 4.65 |
| Outside the impacted area | 902 | 2.61 | 2 | 2.85 | 0 | 24 |
| – in log form (after adding 1) | 902 | 1.02 | 1.10 | 0.73 | 0 | 3.22 |
| Suppliers of direct suppliers | 902 | 618.69 | 85.5 | 1,499.49 | 0 | 12,908 |
| – in log form (after adding 1) | 902 | 4.51 | 4.47 | 2.15 | 0 | 9.47 |
| Number of clients | | | | | | |
| In the impacted area | 902 | 3.63 | 2 | 7.33 | 0 | 90 |
| – in log form (after adding 1) | 902 | 1.06 | 1.10 | 0.88 | 0 | 4.51 |
| Outside the impacted area | 902 | 2.79 | 2 | 3.16 | 0 | 28 |
| – in log form (after adding 1) | 902 | 1.05 | 1.10 | 0.75 | 0 | 3.37 |
| Suppliers of direct suppliers | 902 | 931.67 | 146 | 1,664.09 | 0 | 11,514 |
| – in log form (after adding 1) | 902 | 4.98 | 5.00 | 2.38 | 0 | 9.35 |

In addition, we computed the number of suppliers of the direct suppliers. We were interested in the possible effects of indirect suppliers on recovery from the earthquake because it was reported that the temporary or permanent shutdown of production lines of intermediates affected downstream firms indirectly connected through supply chains. The average and median numbers of suppliers of direct suppliers were 620 and 86.5, respectively, and the maximum was 12,909 (Table 3). The number of clients of direct clients was similarly large. These findings imply that firms in the impacted area were indirectly connected to a substantial number of firms in Japan through supply chains, as reported by Saito (2012).

## 3. EMPIRICAL PROCEDURES

### *Conceptual Framework*

Supply chain networks may affect resilience to and recovery from disasters for the following reasons. First, when firms depend on processed materials, parts, or components from suppliers affected by a disaster, these downstream firms may have to shut down their operations even when they themselves are unaffected by the disaster. This situation may also occur when clients of firms' products are affected by the disaster. Therefore, we hypothesize that a firm's recovery from a disaster becomes more difficult with an increasing number of connections with suppliers and clients within the impacted area. Firms may also have to stop or reduce production when they are not directly connected to affected suppliers but are indirectly connected to affected upstream suppliers or downstream clients through supply chains. Therefore, focusing particularly on suppliers of suppliers and clients of clients, we presumed that when the number of indirect suppliers and clients increases, the likelihood that firms are indirectly affected also increases, thus leading firms to require more time to resume production.

However, supply chain networks are not always harmful to recovery from disasters. There is considerable anecdotal evidence demonstrating that impacted firms received support from clients in the process of recovery. A typical example is Renesas Electronics Co., Ltd., a major producer of microcontrollers for automobiles, with a 44 percent share of the world market. Its main plant in Ibaraki Prefecture was severely damaged by the earthquake, and the resulting complete shutdown of the production of microcontrollers caused a halt of production lines of automobiles outside the impacted area. To support the recovery of Renesas, its clients, including major automobile manufacturers, provided 80,000 man-days of labor to Renesas. As a result, Renesas restarted part of its production on June 10, one month earlier than first predicted, immediately after the earthquake (Renesas, 2011). This example clearly illustrates that connections to clients, particularly those outside the impacted area, may be helpful in obtaining support for recovery.

Connections to clients in the impacted area may also be helpful. The SME Agency (2011) documented the experience of Horio Seisakusho K.K. in Miyagi Prefecture, a small- to medium-sized enterprise with 52 employees that produced optical pickup components and had a 30 percent share of the world market. Because Horio Seisakusho was located at a high elevation, it suffered only limited damage as a result of the tsunami. However, one of its suppliers, Ogatsu Musen Co., Ltd., was located near the sea, and all of its equipment was washed away by the tsunami. Horio Seisakusho let Ogatsu Musen use Horio's idle factory space and production machinery for free. Because of this support, Ogatsu Musen recovered quickly, and as a result, Horio Seisakusho was also able to restart its production quickly, utilizing supplies from Ogatsu Musen. This example demonstrates how supply chain networks within the impacted area can be beneficial to the recovery of both suppliers and clients.

In addition, firms can substitute surviving or new partners for damaged partners after disasters. In our data, 8.1 percent of firms whose suppliers were damaged actually changed their suppliers. In some cases, damaged suppliers themselves asked their competitors to replace them in providing resources to their clients. For example, Iwaki Die-cast Co., Ltd., a supplier of dies and metal parts to Toyota and other firms, was severely affected by the earthquake and forced to stop its operations temporarily. Iwaki Die-cast decided to provide its dies to one of its competitors so that the competing firm could supply metal parts to Iwaki's clients using the dies (*Kahoku Shimpo*, October, 29, 2012). Uchida, a supplier of metal parts for the automobile industry, took the same action (Bloomberg, March, 13, 2012).

Finally, supply chain networks within the impacted area may generate benefits from agglomeration through information spillovers, lower transportation costs, and labor pooling (Marshall, 1890). These standard benefits from agglomeration arise even after disasters, and hence intraregion supply chains can be helpful to recovery from disasters.

The arguments above suggest that the effect of supply chain networks on recovery is not necessarily clear and that different types of supply chain networks affect recovery differently. Therefore, we distinguish between partners (i.e., suppliers or clients) inside the impacted area, partners outside the impacted area, and partners of direct partners. We then estimate the effect of the number of each type of partner for each firm on its recovery from the earthquake.

When we examine the effect of partners of direct partners, we do not particularly distinguish between those inside and those outside the impacted area for the following reason. As Saito (2012) finds, supply chain networks in Japan have a small-world feature in that firms are connected with many other firms by just a few steps through the supply chains. Thus, indirect partners outside the impacted area are likely to be connected to firms in the impacted area that are damaged by the earthquake. As a result, having indirect partners outside the impacted area may increase the probability of the disruption of supply and demand, just as indirect partners inside the area do. Therefore, the number of partners of direct partners, regardless of their location, can be a measure of the size of the supply chain network for each firm, which is related to the probability that the supply chains of the firm are disrupted in the wake of disasters.

### *Estimation Methods*

To examine the questions raised in the previous subsection, we estimate parameter values for the following equation:

$$Recovery_i = \beta_0 + \beta_1\, Network_i + \beta_2 X_i + \varepsilon_i. \tag{1}$$

$Recovery_i$ is a measure of recovery from the disaster for firm $i$, that is, either the number of days that passed before resuming production after the earthquake (the recovery time) or sales growth from the pre- to postearthquake period. *Network* is a set of variables related to supply chain networks, such as the number of suppliers in the impacted area, the number of suppliers outside of the area, and the number of suppliers of direct suppliers, along with the corresponding numbers for clients. For the recovery time and the number of suppliers and clients, we add one and take logs, assuming a quasi-log-linear relationship. We must add one before taking logs because these variables are zeros for some firms. The network variables are correlated with each other, and the correlation coefficient for some pairs is close to 0.7.[3] To avoid possible multicollinearity, we experiment with several specifications in which only a subset of the network variables are used.

We further examine whether the effect of supply chain networks varied depending on the level of damage suffered by a firm. For this purpose, we included in *Network* interaction terms between one of the network variables and dummy variables for the level of damage: completely destroyed, half destroyed, partially damaged, and not damaged. Because the inclusion of many interaction terms can cause multicollinearity, we focus on one particular type of network and excluded other types in each regression of this type.

$X$ is a set of control variables. To control for the effect of firm size and productivity on recovery from disasters, we include the number of workers and sales per worker in 2010,

[3]The correlation matrix can be obtained upon request.

both in log form.[4] Growth in sales and employment prior to the earthquake from 2005 to 2010 were also included because these variables may capture firms' potential capability for recovery. In addition, we incorporate dummy variables representing the level of damage, that is, dummies for completely destroyed, half destroyed, partially destroyed, and not destroyed by the tsunami. Finally, industry and city dummies are included.

We employ a Tobit estimation to examine effects on the recovery time because the minimum of the log of the recovery time plus one is zero and the maximum is log 331, where 330 is the maximum number of days after the earthquake (Section 2). When sales growth is used as the dependent variable, we employ an ordinary least squares (OLS) estimation.

A potential problem in estimating the effect of networks is endogeneity of network variables. In this study, there should be no reverse causality, that is, causality from recovery to networks, because our network variables were collected six years before the earthquake, and damage was exogenously caused by the earthquake. Another source of endogeneity is unobservable factors that affect both the recovery and supply chain networks of each firm. However, growth in sales and employment prior to the earthquake can largely control for firms' potential recovery capabilities, whereas industry and city dummies can control for industry- and location-specific characteristics that most likely affect network characteristics. Therefore, biases due to endogeneity are not expected to be large in this study, although we still test for endogeneity using Smith and Blundell's (1986) method, as discussed later.

## 4. RESULTS

### *Effects on the Time Not in Operation after the Earthquake*

The benchmark effects of the number of suppliers and clients on the number of days not in operation after the earthquake—or the recovery time, our (inverse) measure of short-term recovery—are shown in column 1 of Table 4. As we indicated in Section 2, the median recovery time was five days (Table 3). Further, the recovery time was zero days for 30 percent of the firms and less than 30 days for approximately 90 percent of the firms. Therefore, the recovery time is a measure of short-term recovery for most firms. Columns 2 and 3 of the same table indicate the effects of the number of suppliers and clients separately to avoid possible multicollinearity. In either case, the effects of the dummies for the level of damage were highly significant, whereas the effects of other controls, such as the number of workers and sales, were insignificant.

The effect of supply chain networks varied depending on their characteristics. Networks within the impacted area, measured by the number of suppliers or clients in the area, had no significant effect on recovery. This lack of significance most likely occurs because of canceling between the negative effect on recovery (due to the disruption of supply and demand from damaged firms) and the positive effects (due to the provision of support for recovery from network members, the increased possibilities for the substitution of supply and demand within supply chain networks, and agglomerated regional networks).

[4] Another way to distinguish between the effects of supply chain networks and firm size is to use the ratio of the number of suppliers (clients) to a measure of firm size such as the number of workers. However, using both the number of suppliers (clients) in log form and the number of workers in log form as independent variables yields the same results as obtained from using both the number of suppliers (clients) relative to the number of workers in log form and the number of workers in log form. Therefore, our key independent variable is the number of suppliers (clients), without taking their ratio as a measure of firm size.

TABLE 4: Effects of Supply Chain Networks on Recovery from the Earthquake Dependent Variable: Log (Number of Days without Operation after the Earthquake + 1)

| | (1) | (2) | (3) |
|---|---|---|---|
| Completely destroyed | 2.119*** | 2.159*** | 2.114*** |
| | (0.511) | (0.508) | (0.516) |
| Half destroyed | 1.938*** | 1.951*** | 1.912*** |
| | (0.306) | (0.319) | (0.305) |
| Partially damaged | 1.101*** | 1.098*** | 1.092*** |
| | (0.244) | (0.247) | (0.235) |
| Completely destroyed by tsunami | 1.111*** | 1.080*** | 1.118*** |
| | (0.352) | (0.342) | (0.349) |
| Log (sales per worker in 2010) | −0.247 | −0.252 | −0.246 |
| | (0.221) | (0.221) | (0.219) |
| Log (number of workers in 2010) | 0.0455 | 0.0387 | 0.0594 |
| | (0.135) | (0.141) | (0.134) |
| Growth in sales from 2005 to 2010 | 0.00329 | 0.325 | 0.313 |
| | (0.00241) | (0.257) | (0.251) |
| Growth in the number of full-time workers from 2005 to 2010 | 0.00178 | 0.161 | 0.230 |
| | (0.00374) | (0.374) | (0.390) |
| Log (number of suppliers in impacted areas + 1) | 0.117 | 0.108 | |
| | (0.0913) | (0.0790) | |
| Log (number of suppliers outside impacted areas + 1) | −0.282** | −0.351*** | |
| | (0.133) | (0.126) | |
| Log (number of suppliers of direct suppliers + 1) | 0.0624* | 0.0814** | |
| | (0.0331) | (0.0348) | |
| Log (number of clients in impacted areas + 1) | 0.0299 | | 0.0539 |
| | (0.0789) | | (0.0631) |
| Log (number of clients outside impacted areas + 1) | −0.233*** | | −0.305*** |
| | (0.0651) | | (0.0926) |
| Log (number of clients of direct clients + 1) | 0.0598** | | 0.0678** |
| | (0.0239) | | (0.0275) |
| Number of observations | 902 | 902 | 902 |
| Pseudo $R$ squared | 0.151 | 0.149 | 0.149 |
| Log-likelihood | −1,321 | −1,324 | −1,326 |

*Notes:* The results were obtained from Tobit estimations. Robust standard errors clustered within cities are in parentheses. Industry and city dummies were included as independent variables. *, **, and ***indicate significance at the 10, 5, and 1 percent levels, respectively.

In contrast, networks with firms outside the impacted area, as measured by the number of suppliers or clients outside the area, significantly decreased the time required for recovery. This significant result is clearly because impacted firms were less likely to face shortages of supplies or demands and more likely to receive support when they were connected with more undamaged firms outside the impacted area. Moreover, networks with suppliers and clients outside the impacted area enabled impacted firms to substitute for damaged suppliers or clients in the impacted area.

Finally, the number of suppliers of direct suppliers and clients of direct clients is found to delay the recovery. This finding implies that as indirect supply networks expand, that is, as impacted firms are connected with more firms indirectly through supply chains, the impacted firms are more likely to be connected with any damaged firm and thus to face a shortage of supply or demand. The negative effect of indirect networks on recovery was more evident than the effect of direct networks because support from indirect suppliers cannot be expected, unlike support from direct suppliers.[5]

*Testing for Endogeneity*

We further examined the effect of supply chain networks using each of the network variables separately, in addition to the same controls, in one regression. This experiment was conducted so that we could highlight the effect of each type of network on recovery without the potential for multicollinearity and so that we could test the endogeneity of each of the network variables. As we discussed in Section 3, although our analysis was not contaminated by endogeneity from reverse causality, it might still have been biased due to endogeneity stemming from unobservable factors affecting both supply chain networks and resilience. However, it was difficult to find good instruments, as is often the case. One possibility was sales in the year before data on the supply chain networks were collected (2004 for most firms). This variable was highly correlated with any network variable but was likely to be uncorrelated with the error term in the equation for recovery from the disaster in 2011 after controlling for sales in 2010 and growth in sales from 2005 and 2010. With only one instrument in hand, we could not test for endogeneity of the supply chain variables when there was more than one possible endogenous network variable. By limiting the number of endogenous variables to one in each regression, we were able to test for endogeneity for each network variable using the method of Smith and Blundell (1986), which is an application of the Durbin–Wu–Hausman test to Tobit regressions.

The estimated coefficients of the network variables from the separate regressions, as shown in Table 5, are mostly consistent with the results shown in Table 4. One large difference is that the effect of the number of either indirect suppliers or clients is insignificant. This result is most likely due to correlation between the numbers of direct and indirect suppliers or clients so that the coefficient of the number of indirect suppliers (clients) in Table 5 reflects the positive coefficient for the number of direct suppliers (clients) outside the impacted area shown in Table 4. The bottom row provides the $p$ value of the Smith–Blundell statistic. We could not reject the null hypothesis that the network variable was exogenous for any regression.

*Heterogeneity across Levels of Damage*

Up to this point, we had assumed that each type of network had the same effect, regardless of how much firms were damaged by the disaster. However, the effect of supply chain networks on recovery may be heterogeneous depending on the level of damage. To highlight this possible variation, we used interaction terms between each of the network variables and the dummies for the level of damage, that is, completely destroyed, half or partially destroyed, and not damaged.

We have seen in column 1 of Table 5 that the number of suppliers in the impacted area had no significant effect on recovery. The results in column 1 of Table 6 indicate that this lack of significance was the case regardless of the degree of damage. According to the results in column 2 of Table 6, the negative coefficient for the number of suppliers

[5]When we distinguish between suppliers (clients) of direct suppliers (direct clients) inside and outside the impacted areas, we found that the number of suppliers and clients outside the impacted areas significantly increased the recovery time, while the number of suppliers and clients inside the impacted areas had no significant effect. However, the distinction between the two types of indirect suppliers (clients) may not be meaningful as we discussed in Section 3. Therefore, our analysis is based on estimations without this distinction.

TABLE 5: Endogeneity Test of Variables for Supply Chain Networks Dependent Variable: Log (Number of Days without Operation after the Earthquake + 1)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Log (number of suppliers in impacted areas + 1) | 0.114 | | | | | |
| | (0.0771) | | | | | |
| Log (number of suppliers outside impacted areas + 1) | | −0.162** | | | | |
| | | (0.0783) | | | | |
| Log (number of suppliers of direct suppliers + 1) | | | 0.0247 | | | |
| | | | (0.0221) | | | |
| Log (number of clients in impacted areas + 1) | | | | 0.0646 | | |
| | | | | (0.0748) | | |
| Log (number of clients outside impacted areas + 1) | | | | | −0.145** | |
| | | | | | (0.0628) | |
| Log (number of clients of direct clients + 1) | | | | | | 0.0198 |
| | | | | | | (0.0233) |
| *N* | 902 | 902 | 902 | 902 | 902 | 902 |
| Pseudo $R$ squared | 0.146 | 0.146 | 0.146 | 0.145 | 0.146 | 0.146 |
| Smith–Blundell statistic ($p$ value) | 0.695 | 0.246 | 0.704 | 0.597 | 0.340 | 0.572 |

*Notes:* The results were obtained from Tobit estimations. Robust standard errors clustered within cities are in parentheses. *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively. Other control variables were the dummies for firms being completely damaged, half damaged, partially damaged, and completely damaged by the tsunami, log of sales per worker in 2010 (one year before the earthquake), log of the number of workers in 2010, the growth rate of sales from 2005 to 2010, the growth rate of full-time workers from 2005 to 2010, and industry and city dummies.

TABLE 6: Heterogeneous Effects of Supply Chain Networks on Recovery from the Earthquake Dependent Variable: Log (Number of Days without Operation after the Earthquake + 1)

| X | (1) Number of Suppliers in Impacted Areas | (2) Number of Suppliers Outside Impacted Areas | (3) Number of Suppliers of Direct Suppliers | (4) Number of Clients in Impacted Areas | (5) Number of Clients Outside Impacted Areas | (6) Number of Clients of Direct Clients |
|---|---|---|---|---|---|---|
| Log (X + 1)* completely destroyed | 0.170 | −0.224 | −0.134* | −0.230 | −0.0672 | 0.0198 |
| | (0.215) | (0.174) | (0.0708) | (0.236) | (0.161) | (0.0996) |
| Log (X + 1)* half or partially destroyed | 0.0333 | −0.202*** | 0.0108 | −0.00221 | −0.143** | 0.00688 |
| | (0.0876) | (0.0671) | (0.0304) | (0.0423) | (0.0607) | (0.0266) |
| Log (X + 1)* no damage | 0.121 | −0.128 | 0.0229 | 0.125 | −0.297** | −0.00683 |
| | (0.181) | (0.197) | (0.0609) | (0.218) | (0.125) | (0.0541) |
| *N* | 902 | 902 | 902 | 902 | 902 | 902 |
| Pseudo $R$ squared | 0.145 | 0.147 | 0.146 | 0.146 | 0.147 | 0.145 |

*Notes:* The results were obtained from Tobit estimations. Robust standard errors clustered within cities are in parentheses. *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively. Other control variables were the dummies for firms being completely damaged, half damaged, partially damaged, and completely damaged by the tsunami, the log of sales per worker in 2010 (one year before the earthquake), the log of the number of workers in 2010, the growth rate of sales from 2005 to 2010, the growth rate of full-time workers from 2005 to 2010, and industry and city dummies.

outside the impacted area found in column 2 of Table 5 was primarily due to the negative coefficient for half-destroyed or partially destroyed firms. In other words, networks with suppliers outside the impacted area did not help completely destroyed or undamaged firms. These findings imply that support from suppliers is not helpful to recovery once a firm is completely destroyed and that firms without any damage did not receive any support from suppliers outside the impacted area. The results using the number of clients, as shown in columns 4 and 5 of Table 6, are similar to those using the number of suppliers. One difference is that the number of clients outside the impacted area decreases the recovery time for firms without any damage (column 5), whereas the effect was insignificant for suppliers (column 2). The effect of indirect suppliers and clients was mostly insignificant (columns 3 and 6 of Table 6), as found in Table 5, except for the negative coefficient for the number of indirect suppliers for completely destroyed firms.

### *Effects on Sales Growth*

Next, we examined the effect of supply chain networks on the rate of change in sales from the second and third quarters (i.e., from April to September) of 2010 to the corresponding quarters in 2011. Because the earthquake hit Japan in March 2011, the sales growth reflects sales up to six months after the earthquake. Therefore, the sales growth is a measure of medium-term recovery over a half-year postearthquake period, in contrast to recovery time, which is a measure of short-term recovery within a one-month period. The results from the OLS estimations in Table 7 primarily indicate that both the number of suppliers and the number of clients in the impacted area significantly increased sales growth. In column 1, where both suppliers and clients are incorporated, the effect of the number of suppliers in the impacted area is insignificant. However, this result may be due to multicollinearity between the number of suppliers and the number of clients, as the correlation coefficient between these in the impacted area is 0.51. We also found weak evidence of a positive and significant effect of the number of clients outside the impacted area. The number of suppliers of direct suppliers or clients of direct clients had no significant effect.[6]

We further examine the possible heterogeneous effects of networks on sales growth depending on the level of damage, as we did in the case of effects on the recovery time. We found that networks with suppliers and clients in the impacted area were particularly helpful to firms that were half or partially damaged but were not helpful to either completely destroyed or undamaged firms.[7]

## 5. DISCUSSION

The results shown in Tables 4–7 imply that supply chain networks with firms outside the impacted area contributed to the earlier resumption of production for firms that were not devastated by the earthquake, but they did not contribute to sales growth in the half-year period after the earthquake. By contrast, networks within the impacted area boosted sales recovery for the same type of firms but did not affect the resumption of production. The two sets of results are not necessarily contradictory because the time spans of the two measures of recovery were different, as we mentioned earlier. Therefore, we can conclude that networks within the affected region stimulate medium-term recovery, whereas networks beyond the affected region promote short-term recovery.

[6] When we distinguish between suppliers (clients) of direct suppliers (direct clients) inside and outside the impacted areas, we found that the number of either type had no significant effect on sales growth.

[7] The results are not shown in this paper for brevity but are available from the authors upon request.

TABLE 7: Effects of Supply Chain Networks on Changes in Sales Dependent Variable: Growth Rate of Sales from April–September, 2010 to April–September, 2011

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Log (number of suppliers in impacted areas + 1) | 1.686 | 3.618* | | 3.128* | | | | | |
| | (1.955) | (1.739) | | (1.784) | | | | | |
| Log (number of suppliers outside impacted areas + 1) | 0.167 | 2.610 | | | 1.294 | | | | |
| | (2.614) | (2.976) | | | (1.460) | | | | |
| Log (number of suppliers of direct suppliers + 1) | −0.985 | −1.043 | | | | −0.116 | | | |
| | (0.823) | (0.997) | | | | (0.578) | | | |
| Log (number of clients in impacted areas + 1) | 2.832* | | 3.074** | | | | 3.797** | | |
| | (1.377) | | (1.248) | | | | (1.317) | | |
| Log (number of clients outside impacted areas + 1) | 2.136 | | 2.272 | | | | | 4.034* | |
| | (2.257) | | (2.659) | | | | | (2.275) | |
| Log (number of clients of direct clients + 1) | 0.756 | | 0.510 | | | | | | 1.200 |
| | (0.808) | | (0.930) | | | | | | (0.747) |
| *N* | 883 | 883 | 883 | 883 | 883 | 883 | 883 | 883 | 883 |
| Pseudo *R* squared | 0.136 | 0.129 | 0.134 | 0.128 | 0.126 | 0.126 | 0.131 | 0.129 | 0.130 |
| Smith–Blundell statistic (*p* value) | | | | 0.568 | 0.451 | 0.356 | 0.634 | 0.569 | 0.593 |

*Notes:* The results were obtained from OLS estimations. Robust standard errors clustered within cities are in parentheses. *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively. Other control variables were the dummies for firms being completely damaged, half damaged, partially damaged, and completely damaged by the tsunami, the log of sales per worker in 2010 (one year before the earthquake), the log of the number of workers in 2010, the growth rate of sales from 2005 to 2010, the growth rate of full-time workers from 2005 to 2010, and industry and city dummies.

In Section 3, we discussed several possible channels for the effect of supply chain networks on recovery from the earthquake. Here, we discuss how each channel influenced the effects of supply chain networks found in our analysis.

First, the negative effect of natural disasters can be propagated to firms that are not directly damaged through the disruption of supply chains, even when the firms are only indirectly, and not directly, connected with damaged firms. This argument is supported by the negative effect of indirect suppliers and clients on recovery found in the previous estimations. Moreover, because we had information on how long the supply of materials and intermediates was affected, we were able to directly test whether supply chain networks affected the disruption of supply chains. Specifically, we regressed the number of days (in log form) for which the supply of parts, components, or materials was affected by the earthquake on the network variables and controls using Tobit estimations. The results presented in column 1 of Table 8 indicate that when each network variable was used in a separate regression, the effect of any network variable was found to significantly increase the time period over which supply was disrupted. This finding suggests that firms with more extensive supply chain networks experienced a longer time period of disruption in supply after the earthquake.

The second channel for the effect of supply chains on recovery was support from firms to damaged partners in supply chain networks. We presume that the positive effect

TABLE 8: Effects of Supply Chain Networks on Disruption of Supply Chains Dependent Variable: Log (Number of Days without Supply of Intermediates after the Earthquake + 1)

| Dependent variable | (1) Log (number of days without supply of intermediates after the earthquake + 1) | (2) Dummy variable for receiving support from firms after the earthquake |
|---|---|---|
| Log (number of suppliers in impacted areas + 1) | 0.380* | −0.110 |
| | (0.201) | (0.0818) |
| Log (number of suppliers outside impacted areas + 1) | 0.217* | −0.0777 |
| | (0.111) | (0.129) |
| Log (number of suppliers of direct suppliers + 1) | 0.108*** | −0.00220 |
| | (0.0314) | (0.0399) |
| Log (number of clients in impacted areas + 1) | 0.356*** | −0.134 |
| | (0.117) | (0.0888) |
| Log (number of clients outside impacted areas + 1) | 0.268** | 0.165** |
| | (0.125) | (0.0721) |
| Log (number of clients of direct clients + 1) | 0.117*** | 0.0290 |
| | (0.0441) | (0.0322) |
| Number of observations | 840 | 662 |

*Notes:* In each column, results from six separate regressions using one of the six variables in the table as the key independent variable are integrated. The results were obtained from Tobit estimations in column (1) and from probit estimations in column (2). Robust standard errors clustered within cities are in parentheses. *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively. Other control variables were the dummies for firms being completely damaged, half damaged, partially damaged, and completely damaged by the tsunami, the log of sales per worker in 2010 (one year before the earthquake), the log of the number of workers in 2010, the growth rate of sales from 2005 to 2010, the growth rate of full-time workers from 2005 to 2010, and industry and city dummies.

of suppliers and clients outside the impacted area on the quicker resumption of production found above is partly due to support from undamaged partners outside the impacted area. We further examined the effect of the number of suppliers or clients on whether the firm received human, physical, or financial support from other firms, using a probit estimation. The results presented in column 2 of Table 8 indicate that firms with more clients outside the impacted area were more likely to have received support from firms. This statistical evidence, which is also consistent with the anecdotal evidence of the sort illustrated by the Renesas Electronics example described in Section 3, to some extent supports our presumption regarding the role of support from partner firms in recovery.

Third, supply chain networks enable firms to substitute new partners for damaged suppliers or clients more easily. This is another possible channel we have found for the positive effect of supply chain networks. Using the same firm-level data for the impacted area as used in this study, Nakajima and Todo (2013) found that the quality of new suppliers substituted for damaged suppliers after the earthquake was lower when firms found new suppliers through the Internet or Yellow Pages than when they found them through other firms and industry organizations. This evidence suggests that supply chain networks are helpful to firms in finding more qualified new suppliers when they face supply chain disruption.

Finally, to fully explain the positive effect of supply chain networks within the impacted area in particular, we should also consider the standard effects of agglomeration through information spillovers, lower transportation costs, and labor pooling (Marshall, 1890). These general benefits from regional agglomeration may work more effectively when the chaotic situation in the aftermath of natural disasters is over. Our finding that supply chains within the region promoted medium-term recovery but not short-term recovery is consistent with this argument.

In conclusion, our empirical results confirm four channels for the positive and negative effects of supply chain networks on recovery from natural disasters. Moreover, the results revealed that these channels may balance each other out or one may outweigh the other, depending on the characteristics of the supply chain networks. In the case of supply chains within the region, for example, the positive effect through support and substitution appears to balance the negative effect through network disruption in the short run, but the positive effect through agglomeration outweighs other effects in the medium run. In the case of networks with firms outside the region, the positive effect through support and substitution appears to outweigh the negative disruption effect in the short run.[8] It should be emphasized that in most cases, supply chain networks have a positive net effect on recovery.

## 6. CONCLUDING REMARKS

In this paper, we examined how supply chain networks affect the resilience of manufacturing firms to natural disasters, which has not been previously studied in the literature, using firm-level data from before and after the Great East Japan Earthquake. Supply chain networks negatively influence resilience through network disruption, while positively influencing resilience through support from partners, the substitution of new partners for damaged ones, and regional agglomeration. The results indicate that supply chain networks including firms outside the impacted area contributed to the quicker resumption of production for moderately damaged firms after the earthquake but had only a weak effect on sales growth in the medium term, that is, six months after the earthquake. In contrast, networks within the impacted area increased the sales growth of damaged firms in the medium term, although they were not helpful to firms in terms of resuming production more quickly. The effect of supply chain networks varies depending on the locations of the suppliers and clients and on the time span of the recovery measure (short-term recovery or medium-term sales growth) because each channel works differently in different cases. We conclude that supply chain networks and, in particular, diversified networks with suppliers and clients in different locations, contribute to the resilience of firms to natural disasters.

The positive effect of supply chain networks on economic resilience found in this study has not been well recognized in the literature. The findings of this research suggest that simulation exercises on output losses from disasters, such as that conducted by Hallegatte

[8]Our results also indicate that the number of suppliers outside the impacted areas did not have any significant effect on sales growth. One interpretation is that when firms are connected with more suppliers outside area impacted by a disaster, they can resume production more quickly because of support from suppliers, but their sales do not grow considerably because of limited demand in the impacted areas. One example that is consistent with the interpretation is that of Renesas Electronics Co., Ltd., mentioned in Section 3. Although Renesas resumed production rather early due to massive support from clients, its sales and profits were stagnant even after the resumption. One possible reason for this stagnation, suggested by the Japanese version of *Nikkei* (December 11, 2012), is that the prices of Renesas' products were too low because of the strong bargaining power of its clients. Thus, the strong ties between suppliers and clients did not increase sales for Renesas. In fact, after suffering large losses for a few years, Renesas was finally bailed out by a governmental fund, the Innovation Network Corporation of Japan, and several clients, including Toyota, in 2013.

(2012), should incorporate this positive effect into theoretical models. This inclusion may lower the estimated output losses of firms indirectly affected by disasters through supply chain networks.

There are several caveats for our analysis. First, because one dataset used in this study is at the plant level while the other is at the firm level, our data misspecify the geography of supply–client relationships for multiple-plant firms, as we discussed in detail in Section 2. This data problem may underestimate the effect of networks within the impacted area.

Second, because we have information on the level of damage only for the firms that responded to the RIETI survey, that is, some of the firms in the impacted area, we cannot identify how suppliers and clients for each respondent firm were damaged by the earthquake. Obviously, the effect of damaged suppliers and clients is different from the effect of undamaged ones, but we cannot incorporate the distinction.

Third, although we found benefits from diversifying supply chain networks, the extent to which firms should diversify their supply chain networks remains unclear because we did not conduct any cost–benefit analysis. Clearly, diversifying suppliers and clients across regions is expensive, which is most likely the main reason why many firms have a limited number of suppliers and clients (Section 2). It is expected that future research will investigate firm decisions based on the costs of finding suppliers and clients and the firm's degree of risk aversion. This type of investigation would make it possible to find the optimal level of diversification to maximize the net benefit, that is, the long-term benefits from strengthened economic resilience less the short-term costs.

Finally, although we distinguished between suppliers and clients inside and outside the impacted area, a more detailed geographical classification of suppliers and clients, such as those inside and outside the same industrial cluster, would be helpful to better clarify how the agglomeration effect works for recovery. In addition, although this study focused on interfirm supply chain networks, intrafirm linkages, such as intrafirm locational strategies and contractual relationships within the firm, may also be important to recovery from disasters. These issues are left for future research.

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