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How Do Firms Respond to Supply Chain Disruptions? Evidence from the Great East Japan Earthquake*

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Abstract

Recently, supply chains have been disrupted worldwide. Using 12-year panel data on buyer-supplier linkages in Japan, we study how the Great East Japan Earthquake in 2011 affected firm performance and their supply chains. We focus on buyer firms located outside the disaster area that were not directly hit by the earthquake and compare those firms with and without suppliers inside the disaster area before 2011. Exploiting difference-in-differences designs, we first find that treated firms, on average, were not differentially hurt. This is confirmed with various firm performance indicators including sales, employment, profit, investment, and productivity measures. Second, we find that treated firms increased the share of suppliers located outside the disaster area, which suggests that they substantially adjusted their supplier relationships. Moreover, we show that treated firms disproportionately accumulated new suppliers closer to their headquarters. The results suggest that it is important for firms to swiftly adjust their supplier network when they face huge, sizeable shocks.

Keywords: supply chains; productivity; resilience; natural disasters
JEL classification: E23, F14, O47, R15

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1 Introduction

Recently, there have been a number of major supply chain disruptions such as Brexit, Trump's trade wars, COVID-19 Pandemic, the Ukraine invasion, and extreme weather events associated with climate change. When faced with such events, firms try to adapt in many ways including restructuring their supply chains. Some firms are better at finding alternative suppliers, and they are therefore able to maintain supplies of critical inputs and successfully continue operations even in turbulent times. Other firms, however, fail to find alternative suppliers, which can result in the closure of factories for a certain period of time, as recently documented for the automobile industry when it suffered a severe shortage of semiconductors. Thus, the ability to find alternative suppliers is fundamental to firms' resilience against supply chain disruptions.

As the review of Baldwin and Freeman (2022) point out, evidence in economics literature on how firms cope with supply chain shocks is extremely limited. It is in contrast to the fact that these disruptions are likely to happen more in the future due to climate change and geopolitical reasons. We aim to fill the gap in the literature by studying what impact a major supply chain shock has on (i) firm performance, (ii) firms finding new suppliers and (iii) how these effects are heterogeneous depending on the type of supplier relationships that have been disrupted. In particular, we exploit large-scale firm-level buyer-supplier linkage data before and after the 2011 Great East Japan Earthquake – a canonical large exogenous shock. The damage of the earthquake was localized, unlike recent macro shocks (e.g., the COVID-19 pandemic) which enables us to study supply chain restructuring. We use a difference-in-differences estimation to estimate the impact on firms performance and their supplier choice. Our study provides novel insights into how firms restructure their supply chains in response to shocks and what determines the ability to restructure.

The Great East Japan Earthquake was the largest recorded earthquake in Japan to date that far exceeded expectations. The earthquake, subsequent tsunami, and aftershocks led to an unprecedented number of casualties and demolition of production and sales facilities in the disaster area and damaged the transport infrastructure. It was recorded that 15,859 people were killed, and 3,021 people were listed as missing due to the disaster, as of May 2012. The Japanese government estimated the total capital loss due to the earthquake to be 16.9 trillion yen (USD 200 billion) as of June 2011. The combination of all these factors negatively affected firms in the disaster area. Moreover, while firms located outside the disaster area did not experience large direct negative impact, they did incur important indirect impacts, particularly through their supply chains.

We focus on firms located outside the disaster area and consider a treatment group consisting of firms that had a supplier inside the disaster area before the earthquake. We construct a control group of firms that also had at least one supplier in a different prefecture, but not in the disaster area. We show that this is sufficient to balance the pre-trends, but we also consider alternative more finely matched groups in robustness tests.

We use buyer-supplier linkage information from a private credit reporting company, Tokyo Shoko Research (TSR), on an annual basis. We obtain access to panel data between 2007 and 2018 on the large share of firms in Japan. We observe the suppliers and customers of the firm as well as basic firm characteristics. Also, we supplement firm-level information from the Basic Survey of Japanese Business Structure and Activities (BSJBSA), Minitry of Economy, Trade and Industry (METI). While the disaster primarily affected firms inside the disaster area, which comprised four prefectures, our focus is on those firms located *outside* the area. The group of firms with suppliers inside the area was likely to suffer a strong indirect negative impact, compared to other firms. These buyer firms lost many of their suppliers and had a strong incentive to reshuffle their supply chains.

Our core results are as follows. First, we find surprisingly that treated firms' sales, employment, and productivity were largely unharmed relative to those of the control firms. Although there were negative effects on the aggregate economy, the firms reliant on suppliers inside the disaster zone were resilient. Digging into why this is the case, we find that treated firms were successfully able to replace their lost suppliers quite quickly.

Second, treated firms shifted their suppliers from within the disaster area to those outside and this change persisted even seven years after the earthquake, when the area had largely recovered. These results highlight the importance of swift adjustment of supply chains for firms' resilience against disruptions.

Third, we investigate the spatial distribution of supply chains. Treated firms bring their new suppliers much closer to the headquarters. For example, there is a 14% increase in the number of suppliers within 50 km from their headquarters in the wake of the earthquake. These geographical patterns of adding and dropping suppliers led to the localization of the supply chains. These results speak to firms' choice of suppliers over space.

There are costs and benefits when firms choose nearby suppliers. The benefits are that it is easier for firms to monitor suppliers' activities, solve problems more swiftly, obtain more information on quality, and build up relational capital with suppliers (see Macchiavello, 2022, for a review of recent studies on relational contracts). For example, after the Great East Japan Earthquake, Toyota Motor Corporation created a database of suppliers, i.e., RESCUE (REinforce Supply Chain Under Emergency) System, in order to build up a disaster-resilient supply chain.[1][2] This example shows that firms recognized the importance of acquiring information on suppliers.

On the other hand, the cost of sourcing from nearby suppliers comes from the smaller variety of firms as being able to match with more distant suppliers is likely to lead to better matches and a higher quality-cost ratio. Therefore, there is a trade-off between costs and benefits of having nearby suppliers rather than distant ones. Our results suggest that treated firms put a greater weight on the benefits of geographical proximity, which resulted in so-called *nearshoring*.[3]

The findings on the spatial distribution of suppliers are in line with the fact that firms and governments increasingly recognize the benefits of proximity. The existing studies on within-firm organization (e.g., Giroud 2013; Gumpert et al. 2022; Kalnins and Lafontaine 2013) find the benefits of firms' having key production and R&D plants close to their headquarters. Recent papers on climate change related natural disasters (e.g., Castro-Vincenzi 2022, Indaco et al. 2020, Gu and Hale 2022, and Pankratz and Schiller 2021) posit that there will be more disasters that will further lead to spatial organisation of firms.

This is also the case for cross-border reorganization. Recently, governments have implemented policies to bring key facilities back within national borders in order to strengthen the economy and reduce national security concerns (e.g., US CHIPS and Science Act[4], European Chips Act[5], Japan's Economic Security Promotion Act[6]). These policies are expected to accelerate the movement of deglobalization. Although this study investigates supply chains within a country, the current results indicate that major supplier shocks, such as natural disasters and trade wars, may cause firms to bring the supply chains closer to their headquarters, and motivate us to anticipate that the similar phenomenon would occur in the context of global supply chains. It is more costly to find alternative foreign suppliers after a major disruption, and that incentivizes firms to switch to domestic suppliers.

This study contributes to four strands of the literature. First, this study contributes to the literature on the propagation effects of economic shocks (see, e.g., Acemoglu et al. 2012; Barrot and Sauvagnat 2016; Boehm et al. 2018; Carvalho et al. 2021; di Giovanni et al. 2014; Heise 2016; Magerman et al. 2016). Barrot and Sauvagnat (2016) find economically large estimates of propagation effects for natural disasters. Carvalho et al. (2021) is the most relevant study to our paper. They use the same TSR data during 2010–2012 and find

[1] Yoshioka, Akira. February 16, 2021. "Handotai Shock." The Nikkei Business (in Japanese).

[2] The Japan Times. July 26, 2019. "Toyota looks to develop ways to disaster-proof its supply chains."

[3] Alfaro and Chor (2023) find nearshoring as a consequence of US-China trade wa, which they refer to as "Great Reallocation."

[4] Source: White House (2022).

[5] Source: European Commission (2022).

[6] Source: Cabinet Office (2022).

significant negative effect of the Great East Japan Earthquake on firm sales.

Second, it contributes to the literature on supply chains. Recent papers have investigated supply chain disruptions and resilience against such disruptions. Baldwin and Freeman (2022) provide a review on the literature suggesting that evidence in economics literature is limited thus far (see also, e.g., Antràs and Chor 2022, Elliott and Golub 2022). Grossman et al. (2021) provide a theoretical framework behind supply chain diversification. Elliott et al. (2022) theoretically investigate supply chain fragility, whereas Ksoll et al. (2022) provide empirical evidence exploiting election violence in Kenya and show that firms ramped up shipments just before the election to avoid conflicts. Khanna et al. (2022) and Balboni et al. (2023) are the most relevant studies in this literature. Khanna et al. (2022) investigate the impact of the COVID-19 lockdowns using firm-to-firm transaction data from an Indian state. They show that firms buying more complex products and with fewer available suppliers are less likely to cease transaction relationships. This is in line with our findings of the supply chain adjustment and its heterogeneity based on the transaction duration before the earthquake. While they use lockdown policies across India, we exploit an exogenous localized shock to the supply chains and show that firms in long-term relationships with suppliers located inside the disaster area significantly suffered sales losses. Moreover, we provide evidence of significant nearshoring by treated firms.

Balboni et al. (2023) study major floods in Pakistan and find that exposed firms relocate to areas with lower flood risks, diversify the set of suppliers, and shift the composition of their suppliers towards those located in areas with lower flood risks. Our study differs from their paper in two dimensions. First, we investigate the impact on firms that were indirectly affected through supply chains but not directly damaged by the earthquake, whereas they focus on firms that were directly affected by floods. Second, we obtain different results compared to theirs. We find that treated firms significantly accumulated nearby suppliers after the earthquake without responding to the earthquake risks. The shift was persistent over seven years. Provided that we focus on different settings of supply chain disruptions despite the shared interests in natural disasters, we think that both studies complement with each other to extend this strand of the literature.

Furthermore, the existing studies have examined the endogenous formation of supply chains. Among others, Adao et al. (2020), Bernard et al. (2018), Dhyne et al. (2020), and Sugita et al. (2021) exploit the information on international firm-to-firm transactions. Amiti et al. (2022), Alfaro-Ureña et al. (2022), Atalay et al. (2011), Bernard et al. (2022), Demir et al. (2021), Gadenne et al. (2020), and Lim (2018) focus on domestic transactions. This study uses Japanese large-scale firm-level buyer-supplier linkage data collected by Tokyo Shoko Research (TSR), and provides evidence on the dynamic adjustment of the firm-to-firm transaction network after a huge shock. The TSR data have been used by Bernard et al. (2019), Fujii et al. (2017), Furusawa et al. (2018), and Miyauchi (2021). The dataset used in this study is a 12-year panel spanning 2007 and 2018, whereas the existing papers utilize much shorter panel data. Thus, this is a novel research to examine how firms mitigated the damage caused by a natural disaster by actively adjusting the firm-to-firm transaction networks. We show that supply chain restructuring is a key dimension of firm response to shocks.

Third, this study is also related to the literature on the spatial distribution of economic activity. Eaton and Kortum (2002) is a seminal work that investigated geography and trade between firms. Antràs et al. (2017) and Bernard et al. (2019) further develop the research. Our study contributes to the literature by suggesting that firms indirectly affected by the earthquake accumulated nearby suppliers closer to their headquarters. Also, Davis and Weinstein (2002, 2008) study the impacts of the WWII bombing on Japanese regional distribution of economic activities. Ahlfeldt et al. (2015) and Redding et al. (2011) take a similar perspective while focusing on the division and reunification of Germany. Miyauchi (2021) proposes a microfoundation for the agglomeration of economic activity by focusing on the matching between suppliers and buyers. Panigrashi (2021) constructs a quantitative spatial model to study endogenous production network formation. Arkolakis et al. (2021) provide a theory and investigate how production network shapes the spatial distribution of economic activity. Our study contributes to the literature by focusing on how the transaction network is chosen endogenously by firms after a large earthquake. We find that buyer firms selected nearby suppliers after the Great East Japan Earthquake, thus leading to the supply chain geographical concentration.

Fourth, there have been several previous studies that have investigated the economic impact of the Great East Japan Earthquake. First, Todo et al. (2015) focus on manufacturing firms located inside the disaster area and investigate how supply chain networks affected those firms' resilience to natural disasters. Having more suppliers and clients outside of the disaster area shortened the recovery time in the short run. These findings imply the positive aspect of the supply chains; the presence of supply chains increases the speed of recovery from the shock. Second, Inoue and Todo (2019) and Inoue et al. (2022) focus on the impact on firms located outside the disaster area. Exploiting a computational model, they simulate the effects through supply chains and posit that the magnitude of the indirect effect is substantial. In contrast, Leckcivilize (2012) focus on Japanese automakers in the US and find that they managed to avoid large losses after the earthquake. Our findings add to the discussion by showing that post-disaster adjustment of supply chains is important for firms located *outside* the disaster area to manage disruptions. Firms who could quickly switch to alternative suppliers successfully mitigated the negative impact.

The rest of the paper is structured as follows. Section 2 provides background information on the Great East Japan Earthquake. Section 3 describes the data we use for our empirical analysis. Section 4 presents the results of the impact on firm performance and substantial supply chain adjustment in the aftermath of the earthquake, and Section 5 shows the heterogeneity effects. Section 6 provides the results of the localization of supply chains, and Section 7 presents the empirical analyses to discuss the mechanism. Finally, Section 8 concludes.

2 The Great East Japan Earthquake

2.1 Economic Activities Within the Disaster Area Before the Earthquake

In this section, we explore to what extent the disaster area differed from the rest of Japan in terms of firm activities before the earthquake in 2011. We define the disaster area comprised as four prefectures: Aomori, Iwate, Miyagi, and Fukushima.

These four prefectures' economic structures do not stand out significantly when compared to other parts of Japan. First, prior to the disaster, from 2007 to 2010, these prefectures' GDP ratio to the national GDP remained constant at 4.6%.[7] This share makes sense given that the population of the four prefectures makes up 5.5% of Japan's overall population (as of 2010).[8] Second, in 2009, the firms, establishments, and employees in these four prefectures accounted for 4.9%, 4.5%, and 3.7%, respectively, of the national total.[9] These numbers are roughly proportional in size to the prefectures' share of the national GDP. Third, Figure A.1 shows that there are few differences between the industrial composition of these prefectures and the rest of Japan. Therefore, the earthquake-affected region we will concentrate on can be considered as a typical region of Japan.

2.2 The Size of Damage

On March 11, 2011, the Great East Japan Earthquake occurred off the Pacific coast of the north-eastern part of Japan called the Tohoku region. With a magnitude of 9.0, it was the largest earthquake ever recorded in Japan and the fourth largest worldwide since 1900.[10] The earthquake, subsequent tsunami, and aftershocks caused a tremendous number of casualties and led to property damage on a massive scale, particularly affecting the coastal

[7] Cabinet Office, Government of Japan

[8] Cabinet Office, Government of Japan

[9] Economic Census for Business Frame and Economic Census for Business Activity conducted by Ministry of Economy, Industry and Trade (METI) and Ministry of Internal Affairs and Communications (MIC), Government of Japan

[10] Source: U.S. Geological Survey

areas of the Tohoku region. As of May 2012, it was recorded that 15,859 people were killed, and 3,021 people were listed as missing due to the disaster.[11] The Japanese government estimated the total capital loss due to the earthquake to be 16.9 trillion yen (USD 200 billion) as of June 2011.[12] Among these losses, damage to buildings (e.g., houses, offices, factories and machinery) was estimated at 10.4 trillion yen (USD 123 billion), damage to vital infrastructure (e.g., water, gas, electricity, communication and broadcasting facilities) at 1.3 trillion yen (USD 15 billion), and damage to public capital (e.g., roads, ports and airports) at 2.2 trillion yen (USD 26 billion). As the Tohoku region itself is not known for frequent earthquakes, the occurrence of such a large earthquake and tsunami was unanticipated by both the government and the residents.

Figure 1 Panel (a) shows the geographical distribution of casualties, and Panel (b) shows damaged buildings in each municipality.[13] As Panel (a) shows, casualties were especially concentrated in coastal areas that were exposed to the tsunami, indicating that the damage was not evenly distributed in the hardest-hit prefectures. However, in terms of damage to fixed capital, the damage was more extensive and extended over inland areas. Panel (b) shows that the number of structure collapses was large in a wide range of municipalities. Overall, the four prefectures in the Tohoku region (i.e., Aomori, Iwate, Miyagi, and Fukushima prefectures) were most severely damaged due to the earthquake.[14]

The enormous human and material losses in the earthquake-affected areas seriously harmed economic activity. The real GDP growth rate in the four prefectures along the Pacific coast (i.e., Aomori, Iwate, Miyagi and Fukushima), which were particularly hard hit by the earthquake, was -1.5% in FY2011, a significant decrease from 1.3% in the previous year.[15] That said, the GDP growth rate for the rest of Japan, when excluding these four prefectures, was 2.0% according to National Accounts of Japan in 2014.[16] The earthquake had huge impacts in the affected area but that it had a relatively small effect on Japan's overall economic activity.

Accordingly, firms located inside the disaster area were severely damaged. A survey of those firms conducted by Todo et al. (2015) find that 13.5% of firms were complete or half destructed, 61.3% got partial damage, and only 25.2% were not damaged. White Paper on Small and Medium Enterprises (2011) obtain the similar numbers to confirm the

[11] Cabinet Office, Government of Japan

[12] Cabinet Office, Government of Japan

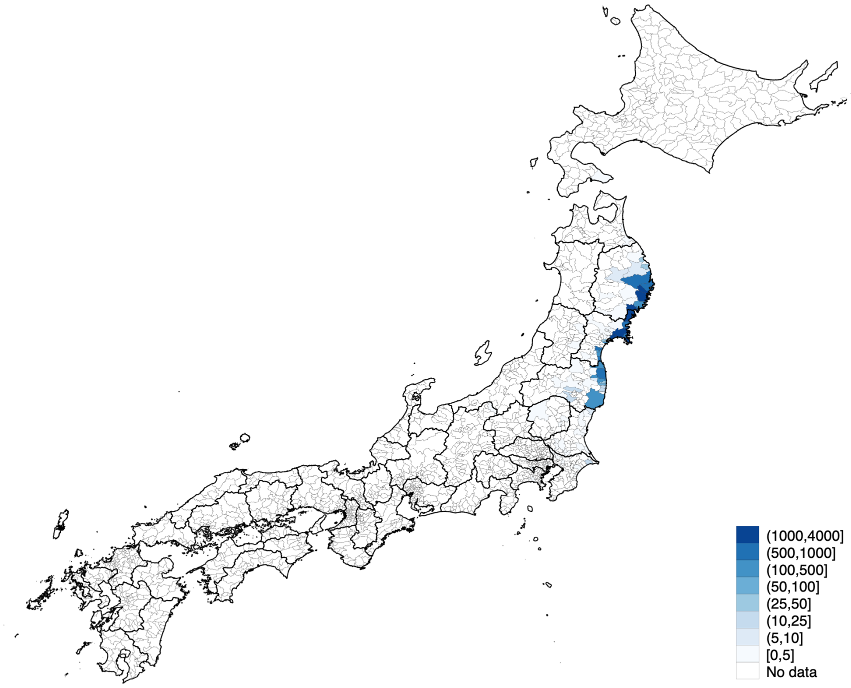
[13] Appendix Figure A.3 depicts the size of other measures that highlight the damage of the disaster.

[14] The nuclear power plant accident occurred in Fukushima.

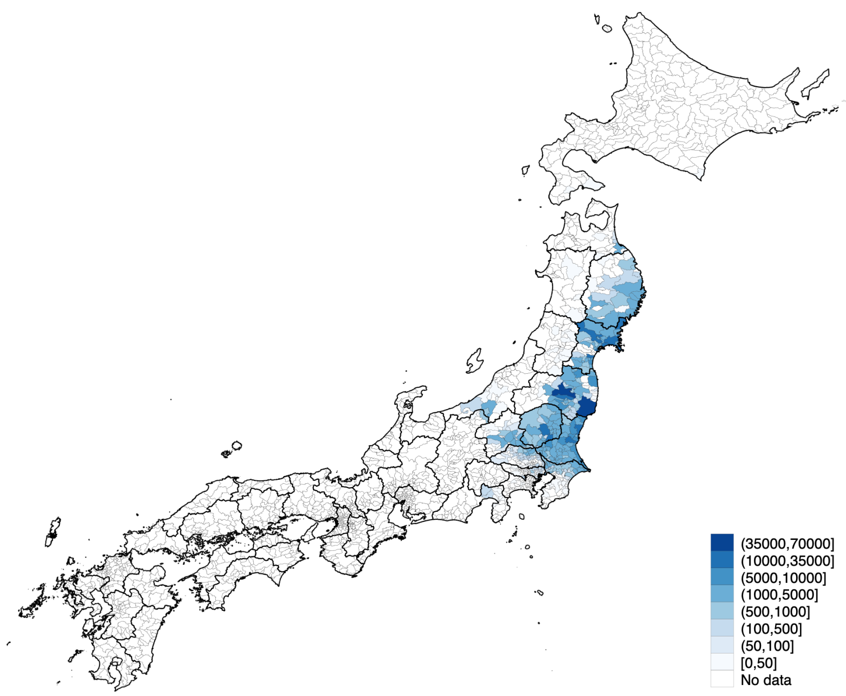
[15] The fiscal year in Japan begins in April and ends in March. As the earthquake occurred at the end of the fiscal year, the economic indicators in FY2010 barely reflect the impact. Therefore, we focus on the information in FY2011.

[16] Cabinet Office, Government of Japan.

Figure 1. Geographical Distribution of Damage by The Great East Japan Earthquake



(a) Fatalities and Missing



(b) Demolished Structures

Note: The figure depicts the distribution of damage caused by the Great East Japan Earthquake. Panel (a) shows the number of fatalities and missing, while Panel (b) represents demolished structures.
Source: White Paper on Disaster Management 2013.

severe damage on firms located inside the disaster area. Economic Census shows that the earthquake resulted in the large decline in the number of firms and employees located inside the disaster area between 2009 and 2012. The number of firms declined by 14%, while the number of employees declined by 8%.

3 Data

3.1 TSR Data

We exploit large-scale buyer-supplier linkage data from Japan. The data sources we use are annual surveys conducted by a private credit reporting company, Tokyo Shoko Research (TSR), and we refer to the data as the TSR data. The TSR data are not census but they cover approximately 70% of all incorporated firms in Japan, including both listed and non-listed firms. From the TSR data, we observe (i) buyer-supplier linkages as describe below; (ii) basic firm characteristics, including sales, employment, the number of establishments, the number of factories, 4-digit industry, profits and geographical address; and (iii) financial statements that allow us to calculate firm-level inputs and outputs.

Firms are asked to report up to 48 transaction partners (24 suppliers and 24 customers) each year. Despite the cutoff, we can back up firm-to-firm transaction network quite well by merging all reports from all firms in the survey. For example, a large firm typically has more than 48 partners, and by using reports from other firms that trade with the firm, we can identify the trading partners for the firm. Therefore, we are able to capture the Japanese firm-to-firm transaction network well.

3.2 Basic Survey of Japanese Business Structure and Activities

We supplement the data with firm-level information from the Basic Survey of Japanese Business Structure and Activities (BSJBSA), Minitry of Economy, Trade and Industry (METI). This survey targets firms with 50 or more employees and capital of 30 million yen (i.e., about 0.2 million dollars) or more. Therefore, it focuses on medium to large-sized firms. The survey includes industries such as manufacturing, mining, wholesale and retail trade, and food services, as well as information and communication services and professional services. From the BSJBSA data, we can observe firm-level sales, the number of employees, firm age, profit, investment, etc., that we use for studying the impact of the earthquake on firm performance in Section 4.2.1. Also, the data allow us to use cost of goods sold (COGS), selling, general and administrative expenses (SG&A), labor cost for production function estimation in Section 4.2.2.

3.3 Summary Statistics

The dataset covers a period of 12 years between 2007 and 2018. We imposed restrictions on the analysis sample. First, as we focus on buyer firms located outside the disaster area, we exclude the firms located inside the disaster area as well as firms located outside the disaster area but that did not have a single supplier. Second, we exclude firms that supplied inputs to buyer firms located inside the disaster area. This restriction is imposed because we focus on supply shocks rather than demand shocks. Third, we restrict our sample to firms that had at least one supplier located in a different prefecture. This is to make treated and control firms more comparable. By definition, treated firms had at least one supplier located in a different prefecture. By imposing this restriction, we focus on control firms that share the similar characteristics with treated firms. This sample restriction excludes small businesses that operate locally and trade only with other firms located in the same prefecture. After imposing three sample restrictions, the total number of observations is around 200,000, which indicates that there were approximately 17,000 observations for each year. The unique number of firms in the dataset is 27,477.

Table 1 below shows the summary statistics. The coverage is broad, ranging from small to large firms, and from young to old firms. On average, firms in the sample have about 230 employees, 20 suppliers and 20 customers. The maximum number of suppliers is about 5,000, and that of customers is about 2,000. This confirms that we capture domestic buyer-supplier linkages well beyond the cutoff.

Table 1. Summary Statistics

	# of obs	Mean	Median	SD	p90	p10
Firm sales	193,221	12,729,775.609	4,347,736	48,201,626.840	24,124,608	1,150,000
Firm age	201,642	41.824	43	19.167	65	14
Firm size	200,963	228.529	111	522.032	442	53
Total # of links	201,646	41.234	25	71.771	83	7
# of suppliers	201,646	20.343	12	37.551	39	1
# of customers	201,646	20.891	10	54.206	41	0

Note: Sales unit is 1,000 yen. Firm size is defined as the number of workers.

4 Empirical Results

4.1 Identification Strategy

We conduct a difference-in-differences estimation to investigate how firms responded to the earthquake. As before, we focus on buyer firms located outside the disaster area. Firms in the treatment group are those that had a supplier inside the disaster area before the earthquake. In contrast, firms in the control group are those that did not have a supplier inside the disaster area during the same time window. Because we are interested in the impact of supply shock caused by the earthquake, we exclude firms that supplied inputs to buyer firms inside the disaster area. Additionally, we restrict the sample to buyer firms that had at least one supplier in a different prefecture. This is to make the firms in treatment and control groups more comparable.

We run the following regression:

$$Y_{it} = \sum_{t=-3}^{8} \beta_t D_i T_t + \sum_{t=-3}^{8} \gamma_t X_i^{2010} T_t + \eta_i + \tau_{jkt} + \epsilon_{it}, \tag{1}$$

where D_i is a dummy that takes the value of 1 if a firm i had a supplier inside the disaster area before the earthquake (and 0 otherwise), and T_t is a time dummy that takes the value of 1 for year t excluding 2010 as the base year. X_i^{2010} refers to firm covariates including firm age, distance to the disaster area, and the total number of transaction partners at the level of 2010. We also include firm fixed effects, η_i, and prefecture-4-digit industry-year fixed effects, τ_{jkt}. The standard errors are two-way clustered with prefecture and 2-digit industry.

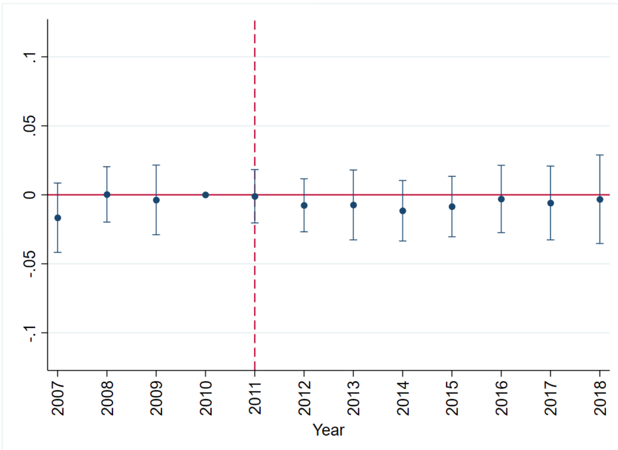
4.2 The Impact on Firm Performance

4.2.1 Firm Performance

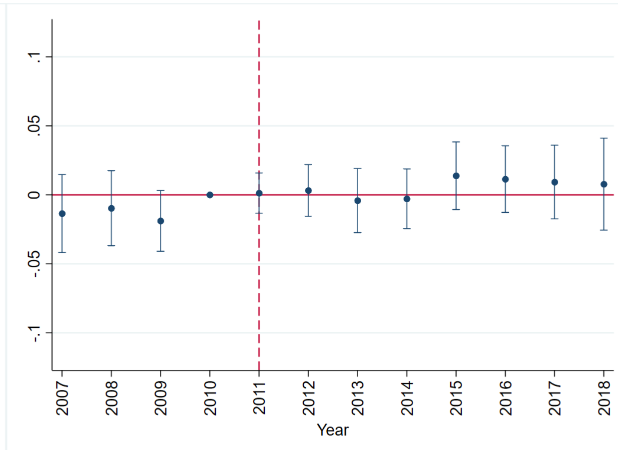
We begin by investigating the impact of the disaster on firm performance indicators. The disaster caused damage to the economic activities inside the disaster area and the rest of the country. The question here is whether the disaster had differential effects between the treatment and control groups. To answer this, we exploit a difference-in-differences estimation based on equation (1) and use firm sales, the number of employees, and TFP as outcomes. Figure 2 then shows the results. Panel (a) uses log total sales as the outcome, and Panel (b) uses log number of employees. Panel (c) uses investment measured as capital expenditure divided by the number of employees, and Panel (d) uses profit measured as ordinary income divided by asset.

The results are as follows. First, we do not find significant pre-trend for all outcomes. This suggests that both the treated and control firms were similar in terms of sales, employment, and productivity measures before the earthquake. Second, and surprisingly, for all of the four outcomes, the coefficients in the post-disaster period are insignificant. This implies that the earthquake did not differentially damage treated firms' performance compared to similar firms in the control group.

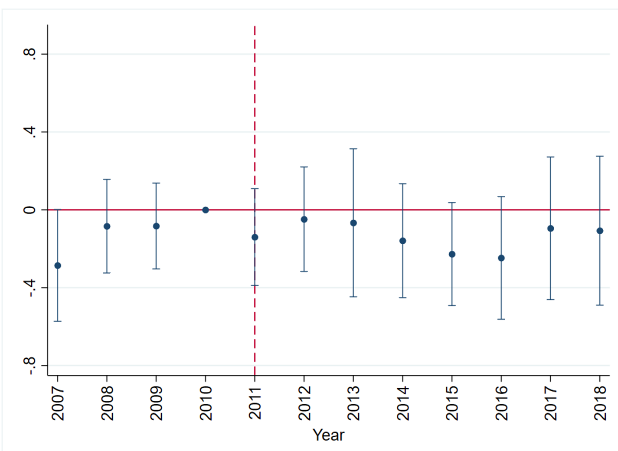
Figure 2. The Impacts on Firm Performance



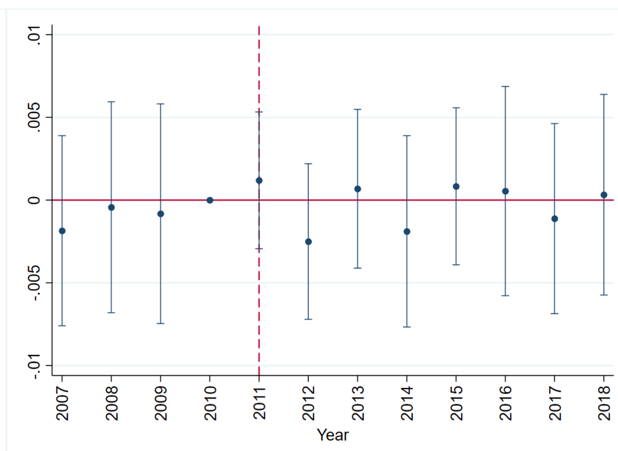
(a) Log Sales



(b) Log Employment



(c) Investment



(d) Profit

Note: This figure plots the coefficients of difference-in-differences estimation. Four panels correspond to (a) log sales, (b) log number of employees, (c) capital expenditure divided by the number of employees, and (d) ordinary income divided by asset. The whiskers indicate the 95% confidence intervals based on the clustering in the 2-digit industry code and prefecture code, while the dots indicate the point estimates. The red vertical dotted line represents the year when the earthquake occurred.

The result of Panel (a) is in contrast to the finding in Carvalho et al. (2021), where they find a significant negative impact on firm sales using the TSR data between 2010 and 2012. We would like to point out two things to shed light on the difference. First, this paper combines the BSJBSA data with the TSR data, and the resulting sample consists of relatively larger firms compared with the original sample of the TSR data. Larger firms may have had more capacity to mitigate the damage caused by the earthquake. Having said that, we still contribute to the literature by using various performance outcomes. This paper investigates the impact on firm sales, employment, profit, and investment, whereas Carvalho et al. (2021) focus on firm sales.

Second, Kawakubo and Suzuki (2024) exploit the TSR data from 2007 to 2018 (Carvalho et al. use the TSR data from 2010 to 2012) and obtain the similar results with the current paper. The authors explain in detail that this is because they utilize updated information in their dataset compared to Carvalho et al. by incorporating late responses from firms. As a feature of the firm-level surveys, some firms respond in later years, which is not unique to the TSR data but is also the case for similar firm-level datasets, including Orbis. By using the data until 2018, they manage to increase the number of non-missing values by about 25% compared to the dataset used in Carvalho et al. (2021).

4.2.2 Productivity Measures

We then turn to examine the impact on firm-level productivity measures. In the analysis, we focus on total factor productivity (TFP) and labor productivity. For TFP, we use the approach proposed by Ackerberg, Caves, and Frazer (2015) (hereafter ACF) as our main measure. The ACF approach addresses the multicollinearity problems inherent in the methods of Olley and Pakes (1996, OP) and Levinsohn and Petrin (2003, LP). To ensure the robustness of our results, we also estimate productivity using the OP and LP approaches. In addition, we use the one-step Generalized Method of Moments (GMM) procedure proposed by Wooldridge (2009), which simplifies the two-step procedures of OP, LP, and ACF.

In order to estimate the production function, it is necessary to deflate the variables used. Therefore, we use the JIP Database 2023 provided by RIETI (The Research Institute of Economy, Trade and Industry) to create deflators for sales, intermediate inputs, value added, and capital investment, thus deflating each variable. The deflators are calculated as the ratio of nominal to real values provided in the JIP Database. The real net capital stock is created following Nishimura et al. (2005) using real capital investment. All deflators are based on the year 2011. Additionally, these deflated variables are winsorized at the 1% level on both sides to mitigate the influence of outliers. Furthermore, we obtain information on industry-specific man-hours per person from the JIP Database and multiply it by the number of employees to calculate the total labor input for each firm. For labor productivity, we divide either sales or value added by the number of employees.

Figure 3 shows the results. For both TFP and labor productivity measures, the coefficients for the post-disaster period are not statistically significant. Additionally, in the pre-disaster period, the coefficients for both measures are generally not statistically significant, suggesting no significant pre-trend differences between the treatment and control groups. These results indicate that the earthquake did not discriminately damage the productivity of the treated firms relative to similar firms in the control group.

4.2.3 Robustness checks

To further confirm that treated firms were not differentially hurt by the earthquake, we have conducted several robustness checks. We have conducted propensity score matching to ensure that firms in treatment and control groups become similar. Estimation results after matching are consistent with our findings before matching (shown in Online Appendix). All of these results confirm that treated firms did not sustain significant damage to their performance.

In the next subsection, we explore how firms coped with the earthquake. In particular, we focus on whether treated firms found alternative suppliers located outside the disaster area. If firms were able to quickly replace suppliers located inside the disaster area with new ones located outside the disaster area, then they could successfully manage the disruptions caused by the disaster.

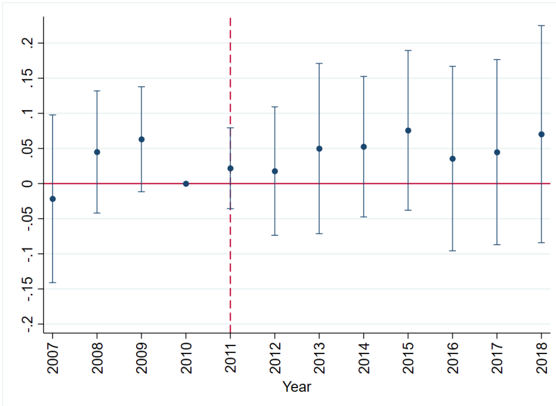
4.3 Restructuring of Supply Chains

4.3.1 Numbers of Suppliers: Outside the Disaster Area vs Entire Country

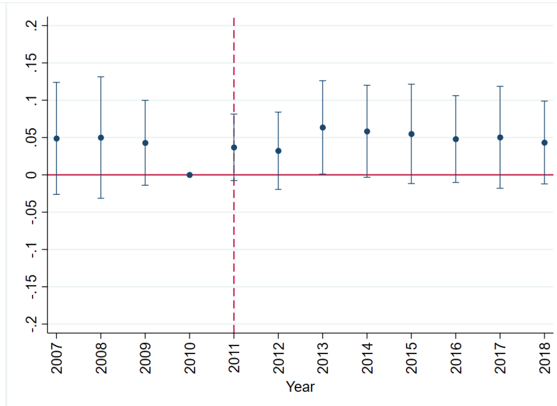
We study treated firms' restructuring of their supply chains. As before, treated firms are defined as buyer firms located outside the disaster area that had a supplier inside the disaster area before the earthquake occurred. We use equation (1) to exploit a difference-in-differences estimation. For the outcome, Y_{it}, we use the share of suppliers located outside the disaster area, i.e., the number of suppliers located outside the disaster area divided by the total number of suppliers in the whole of Japan. If firms did not have new suppliers located outside the disaster area, the share would not rise.

Figure 4 shows the results. The coefficients for 2011–2018 are significant and positive. Also, the coefficients persistently increase from 2011 to 2018. Thus, treated firms did not return to suppliers located inside the disaster area, and they continued adding new suppliers located outside the disaster area after the earthquake. This implies substantial churning of

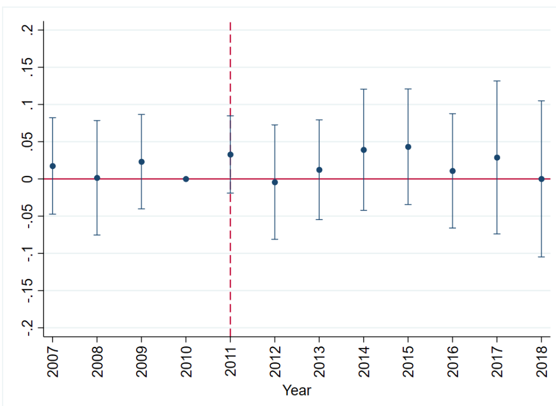
Figure 3. The Impacts on Firm Performance (Productivity)



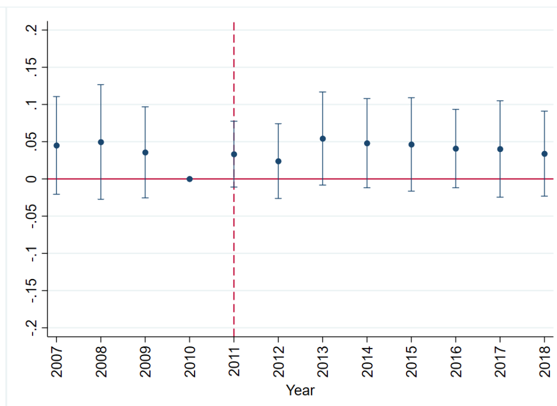
(a) ACF Productivity



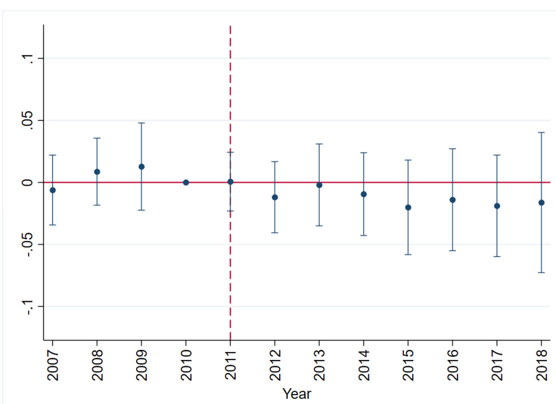
(b) LP Productivity



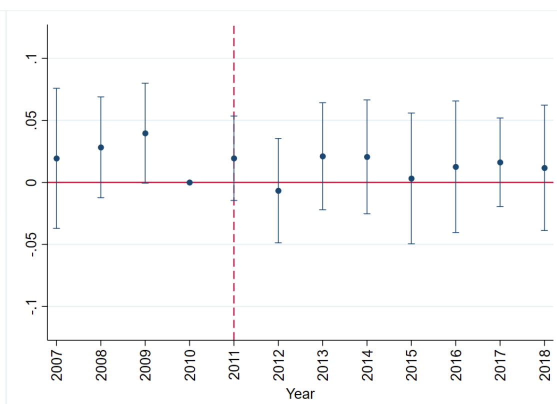
(c) OP Productivity



(d) Wooldridge Productivity



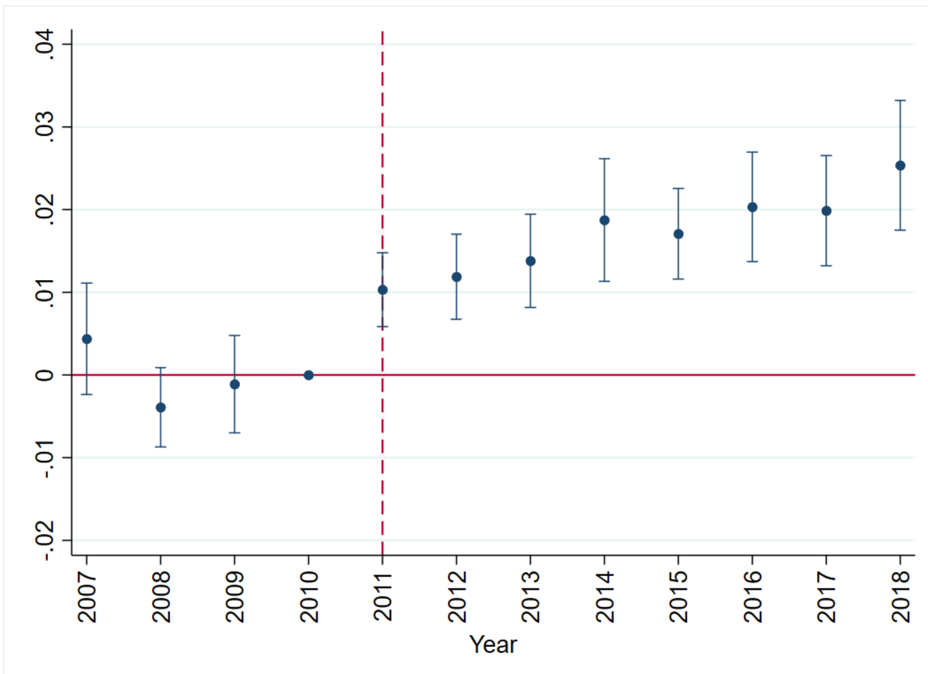
(e) Labor Productivity (Sales per worker)



(f) Labor Productivity (VA per worker)

Note: This figure plots the coefficients of difference-in-differences estimation. Four panels correspond to (a) productivity estimated following the method of Ackerberg, Caves, and Frazer (2015), (b) productivity estimated following Levinsohn and Petrin (2003), (c) productivity estimated following Olley and Pakes (1996), (d) productivity estimated following the method of Wooldridge (2009), (e) labor productivity measured as sales divided by the number of employees, and (f) labor productivity measured as value added divided by the number of employees. The whiskers indicate the 95% confidence intervals based on the clustering in the 2-digit industry code and prefecture code, while the dots indicate the point estimates. The red vertical dotted line represents the year when the earthquake occurred.

Figure 4. Share of Suppliers Outside the Disaster Area

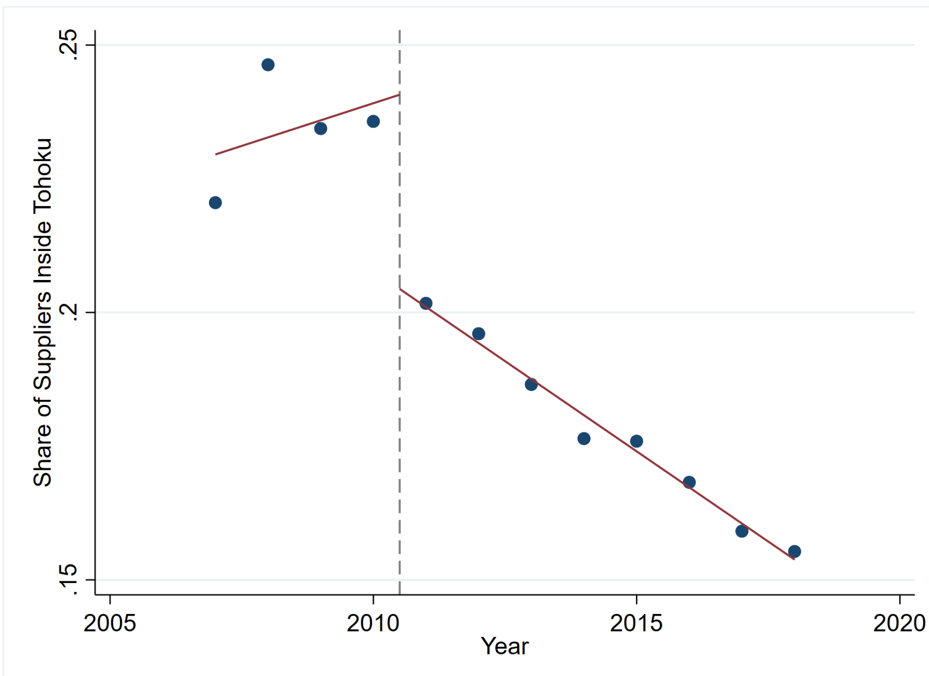


Note: These figures plot the coefficients of difference-in-differences estimation with the share of suppliers outside the disaster area as the outcome. The whiskers indicate the 95% confidence intervals based on the clustering in the 2-digit industry code and prefecture code, while the dots indicate the point estimates. The red vertical dotted line represents the year when the earthquake occurred.

their supply chains, particularly diverting away from the disaster area.

As robustness checks, we have also conducted propensity score matching to ensure that firms in treatment and control groups become similar. As shown in Figure **??**, estimation results after matching are consistent with our findings without matching. These results further confirm that treated firms significantly increased the number of suppliers located outside the disaster area after the earthquake and eventually managed to keep their total number of suppliers despite the disruptions.

Figure 5. Share of Suppliers Inside the Disaster Area



Note: This figure focuses on buyer firms located outside the disaster area that had a supplier located inside the disaster area before 2011, and shows their unweighted share of suppliers located inside the disaster area. The share is defined as the number of suppliers inside the disaster area divided by the total number of suppliers across the whole of Japan.

4.3.2 Share of Suppliers Inside the Disaster Area

As a result, the share of their suppliers located inside the disaster area changed dramatically since 2011. Figure 5 shows treated firms' share of suppliers located inside the disaster area. Two factors should be noted. First, the share drastically declined in 2011, when the Great East Japan Earthquake occurred. Second, after 2011, the share never returned to its original level; instead, it continued to fall. Thus, the year 2011 broke the trend, and the shock appears to be persistent. These results confirm that treated firms substantially restructured supply chains.

5 Localization of Supply Chains

5.1 Number of Suppliers Within Distance Bands (Outside the Disaster Area)

Thus far, we have compared treated firms' sourcing from the disaster area with the rest of Japan, and found that since 2011, treated firms shrank their supply chains inside the disaster area but expanded their supply chains elsewhere. In this subsection, we took a more granular look at the rest of Japan. In particular, we narrow down our focus to examine the geography of the supply chains to explore the change in firms' sourcing decisions.

Excluding the disaster area, we divide the rest of Japan into seven exclusive distance bands: 0–50 km, 50–100 km, 100–200 km, 200–300 km, 300–400 km, 400–500 km, and more than 500 km from firms' headquarters. We then count the number of existing suppliers in year t within each distance band and use these as outcomes. As before, we exploit a difference-in-differences estimation to estimate the impacts of the disaster on the spatial distribution of suppliers. The specification is as follows:

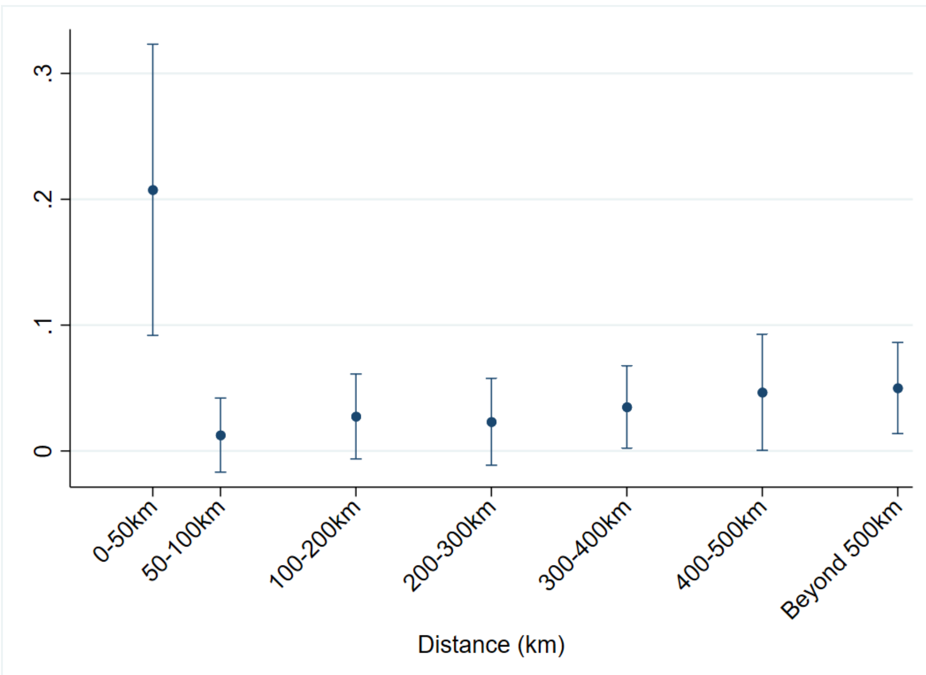
$$Y_{idt} = \beta D_i \times After_t + X_i^{2010}\gamma + \eta_i + \tau_{jkt} + \epsilon_{idt}, \tag{2}$$

where D_i is a dummy that takes the value of 1 if a firm i had a supplier inside the disaster area before the earthquake (and 0 otherwise), and $After_t$ takes the value of 1 for years since 2011 and 0 otherwise. X_i^{2010} refers to firm covariates including firm age, distance to the disaster area, and the total number of transaction partners at the level of 2010. The outcome, Y_{idt}, is the number of existing suppliers in year t within a distance band d. We also include firm fixed effects, η_i, and prefecture-industry-year fixed effects, τ_{jkt}. The standard errors are two-way clustered as before.

Figure 6 shows the estimated results for each distance band. The results are as follows. First, all of the coefficients are significant across distance bands, indicating that the treated firms had more suppliers everywhere compared to similar control firms. Second, and more strikingly, the estimated coefficient is the largest for the closest range, being approximately three times larger than other coefficients. After the disaster, the treated firms had approximately 20% more suppliers within 50 km of their headquarters, compared to the control firms. This is the result for aggregating the post-earthquake period between 2011–2018.

We additionally investigate the dynamics in the accumulation of suppliers over spatial

Figure 6. Log Number of Suppliers Within Distance Bands



Note: This figure plots the coefficients of difference-in-differences estimation with the log numbers of suppliers within distance bands as outcomes. Excluding the disaster area, we split the rest of Japan into the following distance bands: 0–50 km, 50–100 km, 100–200 km, 200–300 km, 300–400 km, 400–500 km, and more than 500 km from firms' headquarters. The whiskers indicate the 95% confidence intervals based on the clustering in 2-digit industry code and prefecture code, while the dots indicate the point estimates of coefficients.

distribution. The specification is as before:

$$Y_{idt} = \sum_{t=-3}^{8} \beta_t D_i T_t + \sum_{t=-3}^{8} \gamma_t X_i^{2010} T_t + \eta_i + \tau_{jkt} + \epsilon_{idt}, \tag{3}$$

where D_i is a dummy that takes the value of 1 if a firm i had a supplier inside the disaster area before the earthquake (and 0 otherwise), and T_t is a time dummy that takes the value of 1 for year t excluding 2010 as the base year. X_i^{2010} refers to firm covariates including firm age, distance to the disaster area, and total number of transaction partners at the level of 2010. We also include firm fixed effects, η_i, and prefecture-industry-year fixed effects, τ_{jkt}. The standard errors are two-way clustered.

5.2 Numbers of New and Dropped Suppliers (Outside the Disaster Area)

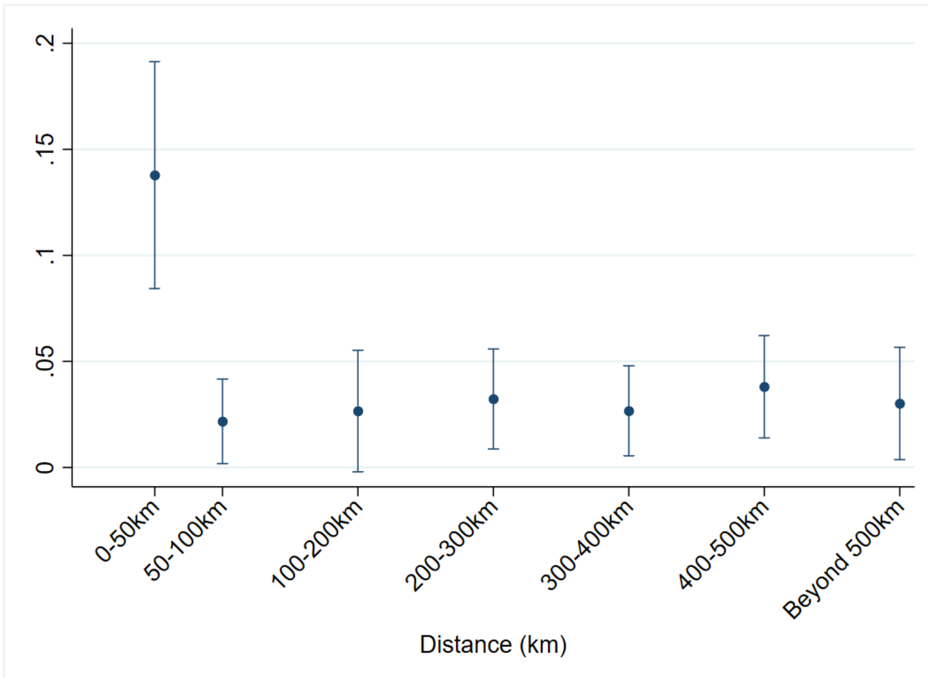
Next, we investigate the numbers of new and dropped suppliers within each distance band. This step seeks to determine whether the accumulation of nearby suppliers is attributable to the fact that firms acquired new suppliers nearby, that firms ceased to trade with distant suppliers, or both. As before, we exclude the disaster area and divide the rest of Japan into seven exclusive distance bands: 0–50 km, 50–100 km, 100–200 km, 200–300 km, 300–400 km, 400–500 km, and more than 500 km from firms' headquarters. New suppliers are defined as the suppliers that treated firms did not trade with in year $t-1$ and then start to trade with in year t. Conversely, dropped suppliers are defined as the suppliers that treated firms traded with in year $t-1$ and then cease to trade with in year t. We then count the numbers of new and dropped suppliers in year t within each distance band.

In order to further investigate the localization of the supply chains after the disaster, we again exploit a difference-in-differences estimation. Here, we additionally control for the numbers of suppliers for all bands at the level of 2010 to examine how the spatial distribution of suppliers has been affected by the earthquake. We modify the specification to be as follows:

$$Y_{idt} = \beta D_i \times After_t + \gamma X_i^{2010} + \sum_{d} \lambda_d Supp_{id}^{2010} + \eta_i + \tau_{jkt} + \epsilon_{idt}, \tag{4}$$

where D_i is a dummy that takes the value of 1 if a firm i had a supplier inside the disaster area before the earthquake (and 0 otherwise), and $After_t$ takes the value of 1 for years since 2011 and 0 otherwise. As outcomes, we use the numbers of new and dropped suppliers within a distance band d. $Supp_{id}^{2010}$ is the number of suppliers in a distance band d in 2010. X_i^{2010} refers to firm covariates including firm age, distance to the disaster area, and total number of transaction partners at the 2010 level. We also include firm fixed effects, η_i, and prefecture-industry-year fixed effects, τ_{jkt}. The standard errors are two-way clustered.

Figure 7. Log Number of New Suppliers Within Distance Bands



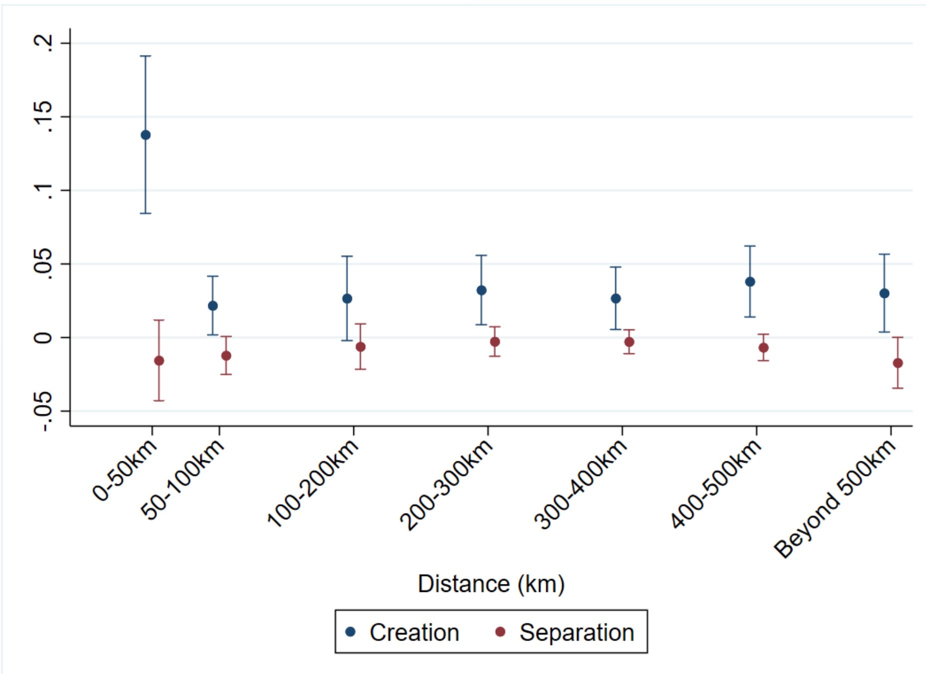
Note: This figure plots the coefficients of difference-in-differences estimation with the log numbers of new suppliers within distance bands as outcomes. Excluding the disaster area, we split the rest of Japan into seven distance bands: 0–50 km, 50–100 km, 100–200 km, 200–300 km, 300–400 km, 400–500 km, and more than 500 km from firms' headquarters. The whiskers indicate the 95% confidence intervals based on the clustering in 2-digit industry code and prefecture code, while the dots indicate the point estimates of coefficients.

First, we examine the impact on the log number of new suppliers in each distance band. Figure 7 shows the results. First, all of the coefficients are significant across all distance bands, indicating that the treated firms had more new suppliers everywhere compared to similar control firms. Second, and more strikingly, the estimated coefficient is the largest for the closest range, being more than twice as large as the coefficient for the most distant range (i.e., more than 500 km). After the disaster, the treated firms had roughly 14% more new suppliers within 50 km from their headquarters, compared to the control firms. This is the result for aggregating the post-earthquake period between 2011–2018.

Second, in Figure 8, we plot the estimated coefficients for the log numbers of dropped suppliers in the same scale. We also plot the estimated coefficients for new suppliers so that we can compare the difference in results. The red dots correspond to new suppliers, while the blue ones correspond to dropped suppliers.

The results are as follows. The coefficients for dropped suppliers are all insignificant across almost all distance bands, whereas we find that those for new suppliers are all significant

Figure 8. Log Number of New and Dropped Suppliers Within Distance Bands



Note: This figure plots the coefficients of difference-in-differences estimation with the log numbers of new and dropped suppliers within distance bands as outcomes. Excluding the disaster area, we split the rest of Japan into seven distance bands: 0–50 km, 50–100 km, 100–200 km, 200–300 km, 300–400 km, 400–500 km, and farther than 500 km from firms' headquarters. The whiskers indicate the 95% confidence intervals based on the clustering in the 2-digit industry code and prefecture code, and the dots indicate the point estimates of coefficients. The red ones correspond to the log number of new suppliers, while the blue ones correspond to the log number of dropped suppliers.

as shown before. Moreover, the sizes of the coefficients are very small, almost 0% for the closest band (i.e., within 0–50 km) to the most distant band (i.e., beyond 500 km). This is in stark contrast to what we find for the number of new suppliers within distance bands. These results imply that the treated firms had a disproportionate number of new suppliers nearby but dropped their old suppliers evenly across space, which is the driving force behind the localization of the supply chains after the earthquake.

5.3 Discussion

The results point to the novel finding that, since the Great East Japan Earthquake, the treated firms have increased their overall number of suppliers outside the disaster area but also localized the supply chains simultaneously. More specifically, firms took on disproportionately more new suppliers nearby while dropping old suppliers evenly across space. Therefore, treated firm significantly *nearshored* after the Great East Japan Earthquake while similar control firms did not.

This appears to contradict the belief that firms would only diversify their supply chains across space when facing risks and uncertainty. However, the findings should be understood in the context of radical changes. First, in line with the recent trend of deglobalization, the deterioration of the US-China relationship has reportedly motivated large firms in the US to bring their production and key facilities back to their home country.[17] Second, climate change has increased the frequency and magnitude of natural disasters and thereby significantly raised the level of uncertainty. This is another force driving the localization of supply chains. Under these conditions, firms have an incentive to geographically concentrate their supply chains. This study contributes to the discussion by providing novel empirical evidence indicating that major supplier shocks, such as the Great East Japan Earthquake, can cause firms to place greater weight on closeness.

6 Conclusion

This study is among the first to investigate how firms respond to a massive supply chain disruption. More specifically, we study the impact of the Great East Japan Earthquake on firm performance and supplier relationships as an exogenous local shock to the supply chains. To this end, we use a long-year panel of Japanese buyer-supplier linkage data between 2007 and 2018 and exploit a difference-in-differences estimation. We first explore the effect of the

[17] Beene, R. July 5, 2022. "American Factories Are Making Stuff Again as CEOs Take Production Out of China." Bloomberg UK. (Last checked on September 20th, 2022)
https://www.bloomberg.com/news/articles/2022-07-05/us-factory-boom-heats-up-as-ceos-yank-production-out-of-china

earthquake on firm performance. The findings indicate that, relative to similar control firms, the performance of treated firms was largely unharmed when using firm sales, their number of employees, and productivity measures as outcomes.

We then investigate the mechanism behind this by examining the extent to which firms found alternative suppliers. After the earthquake, treated firms increased the share of suppliers outside the disaster area, quickly replacing their suppliers inside the disaster area with alternative suppliers outside the disaster area. It implies that there was a sudden shift diverting away from suppliers inside the disaster area to those elsewhere. The effects were not merely temporary but rather persistent over 7 years.

Moreover, the heterogeneity analyses suggest that firms that had longer relationships with suppliers inside the disaster area proved to be more vulnerable to a supplier shock. The findings show a key mechanism behind our first result: Treated firms that switched to new suppliers successfully avoided the damage to their performance, while those that stuck with old suppliers suffered significantly. Based on this finding, one angle for our future work would be to study how firms build up relational capital with their suppliers and how their relationships further affect firm performance.

Third, we investigate the spatial distribution of supply chains. We find that treated firms disproportionately had about 20% more suppliers within 50 km from their headquarters, while similar control firms did not significantly altered their sourcing decision in the wake of the earthquake. Firms accumulated suppliers by adding new suppliers that were disproportionately nearby while dropping old suppliers evenly across space.

There are two implications. First, our findings are in line with the recent movement of deglobalization. Due to higher risks and mounting uncertainty, firms are motivated to bring not only production and key facilities but also suppliers nearby. Second, we anticipate that climate change may also further accelerate the localization of supply chains. We believe that this may present an interesting topic of discussion for future studies.

Finally, we turn to discuss policy recommendations that emerge from our findings. The governments should support firms' search for alternative suppliers after major supply shocks. It would also be beneficial if the governments help firms invest in technologies to collect more information on suppliers' activities. We believe that further research should be conducted to address what policies could mitigate supply chain disruptions at the macro level while also support firms in maintaining their operations at the micro level.

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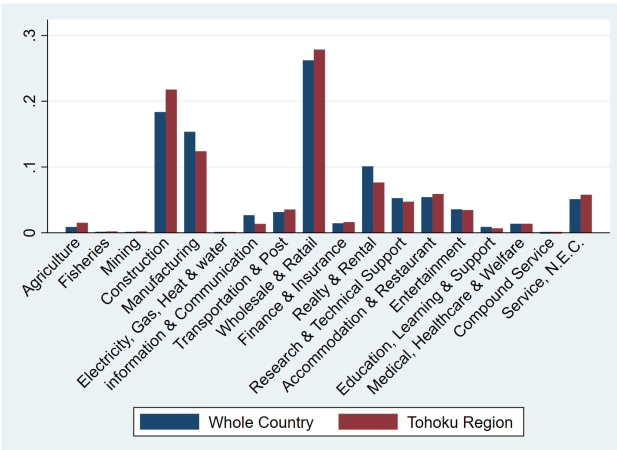
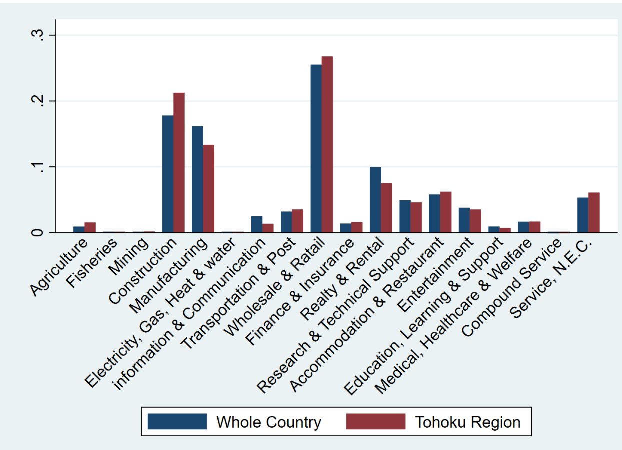
Appendix A Tables and Figures

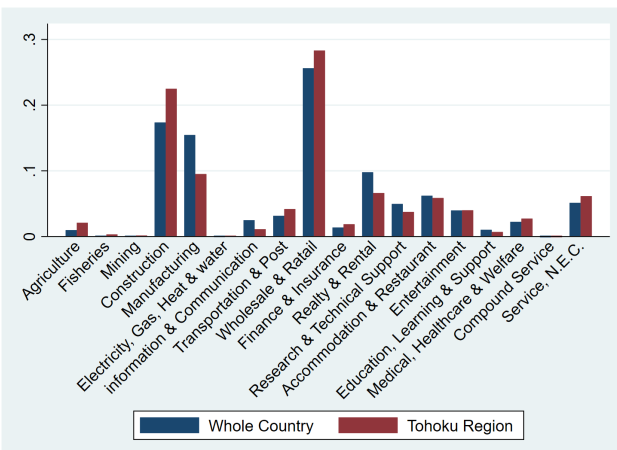
Figure A.1. Share of industries: Entire Country and Disaster-hit Area



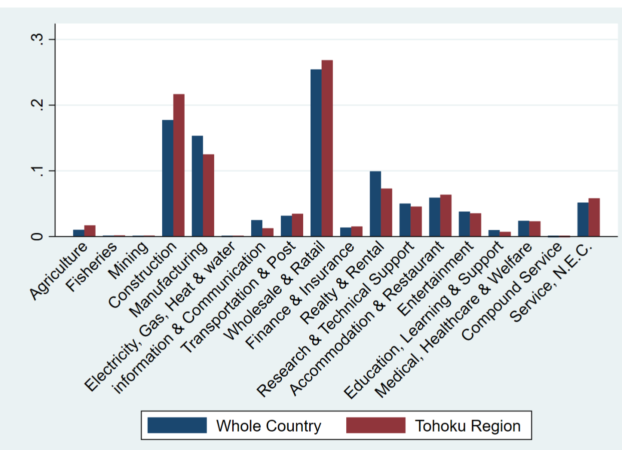
(a) 2009



(b) 2012



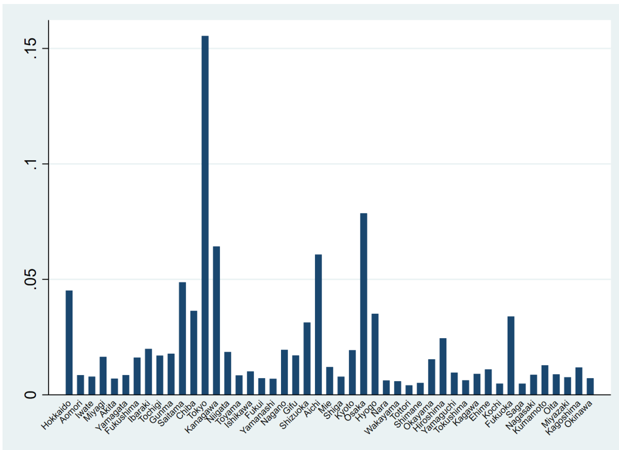
(c) 2014



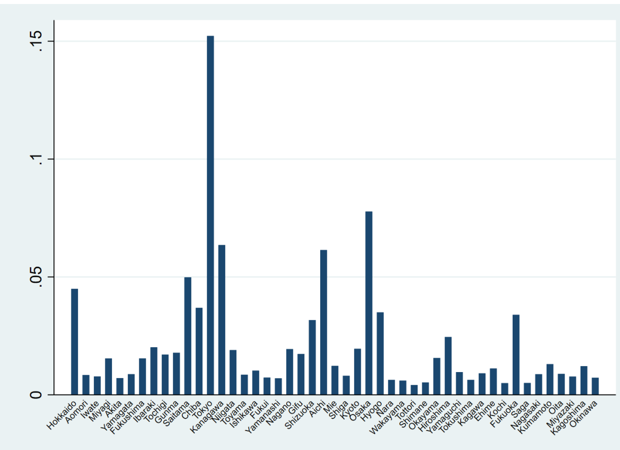
(d) 2016

Note: Each panel shows fraction of firms by industry in the disaster area and entire country, respectively. Red bars are for the disaster area, and blue bars are for the entire country. Panel (a) corresponds to 2009, Panel (b) corresponds to 2012, Panel (c) corresponds to 2014, and Panel (d) corresponds to 2016.
Source: Economic Census for Business Frame and Economic Census for Business Activity conducted by Ministry of Economy, Industry and Trade (METI) and Ministry of Internal Affairs and Communications (MIC).

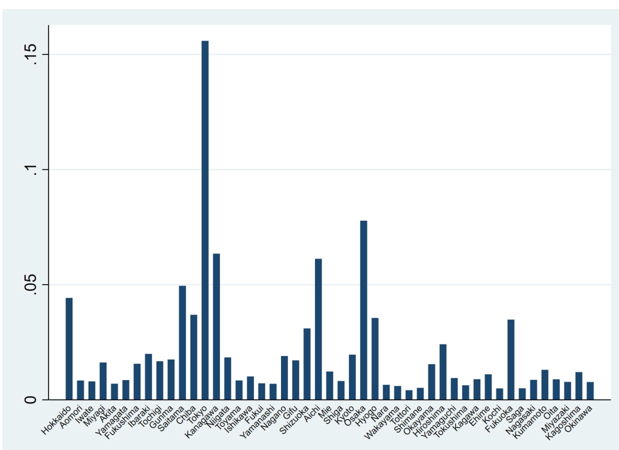
Figure A.2. Share of Firms by Prefecture



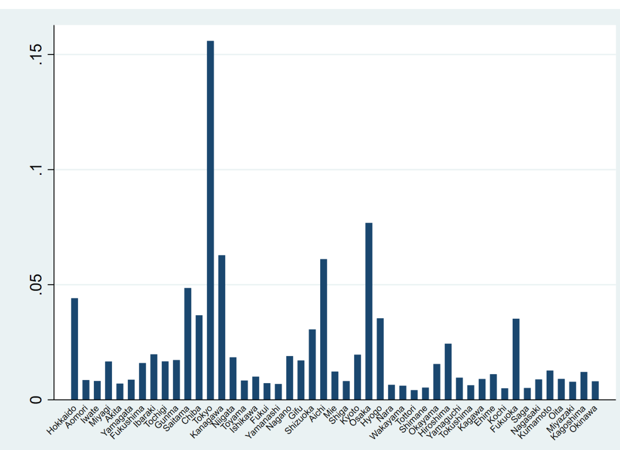
(a) 2009



(b) 2012



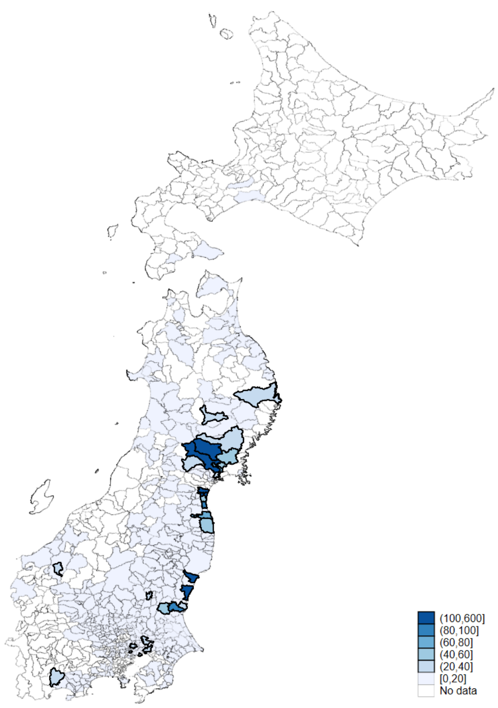
(c) 2014



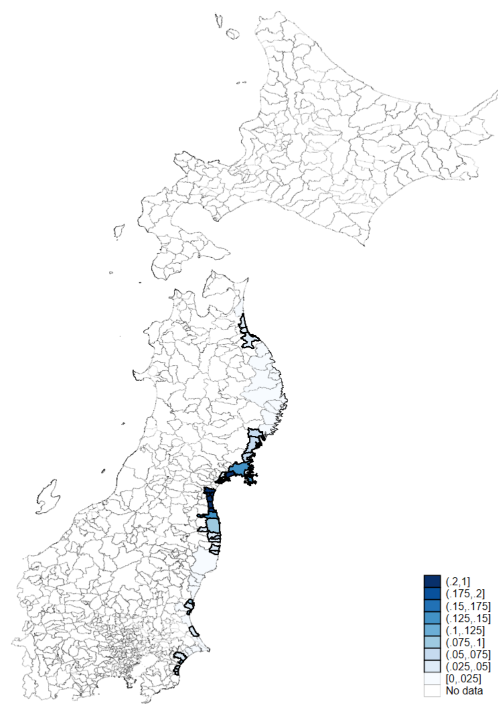
(d) 2016

Note: Each panel shows fraction of firms by prefecture. Panel (a) corresponds to 2009, Panel (b) corresponds to 2012, Panel (c) corresponds to 2014, and Panel (d) corresponds to 2016.
Source: Economic Census for Business Frame and Economic Census for Business Activity conducted by Ministry of Economy, Industry and Trade (METI) and Ministry of Internal Affairs and Communications (MIC).

Figure A.3. The Geographical Distribution of Disaster Damages



(a) Serious and Minor Injuries



(b) Share of Flooded Area

Note: The figure depicts the distribution of the damages caused by the disaster. Panel (a) shows the number of serious and minor injuries, and Panel (b) shows the share of flooded area.
Source: White Paper on Disaster Management 2013.

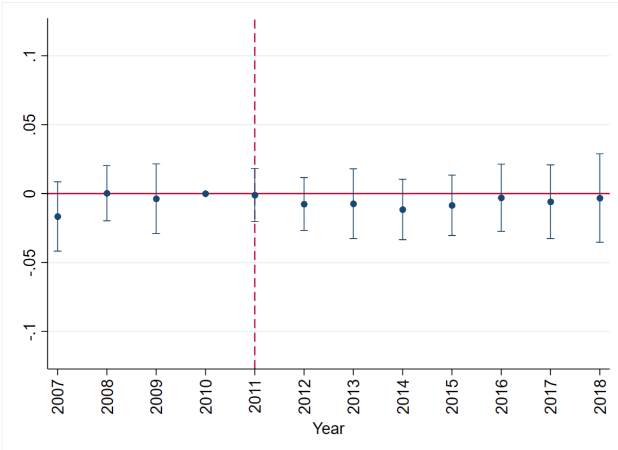
Appendix B Propensity Score Matching Estimation Results

This section provides the results with Propensity Score Matching (PSM) estimation as robustness checks. The treatment and control groups may differ regarding firm size and other characteristics. This difference between both groups could result in biased estimates since firms' supplier choice may be different between the two groups even after controlling for firms' characteristics. The purpose of this section is to mitigate these concerns.

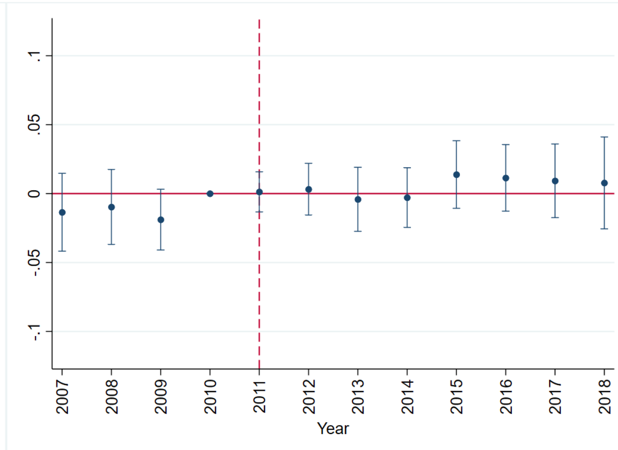
First, we estimate propensity scores with a logit model that controlls for firm age, size, the total number of customers and suppliers, and distance to the disaster area, which we also control for in the baseline estimation. We take the average value of each covariate from 2007 to 2010, i.e., the period before the earthquake. We also control for the 2-digit industry dummy and the prefecture dummy in the estimation. Second, based on the estimated propensity scores, we select firms in the control group to correspond one-to-one to those firms in the treatment group.

The results are as follows. First, Figure B.1 presents the estimation results of firms' performance, which corresponds to Figure 2 in the baseline. Figure B.2 presents the estimation results of firms' performance, which corresponds to Figure 3 in the baseline. Second, Figure B.3 presents the estimation results of firms' restructuring of supplier relationships, which corresponds to Figure 5. Third, Figure B.4 shows the PSM estimation results for log number of new and dropped suppliers within distance bands, which corresponds to the baseline result shown in Figure 8. All results shown here are similar to those obtained in the baseline estimation and confirm that our findings are robust.

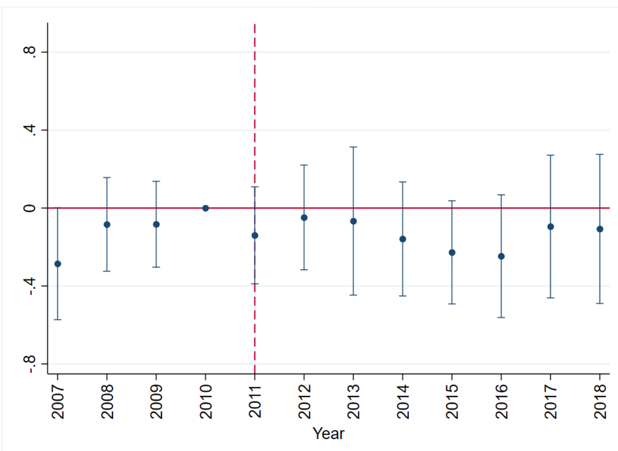
Figure B.1. The Impacts on Firm Performance



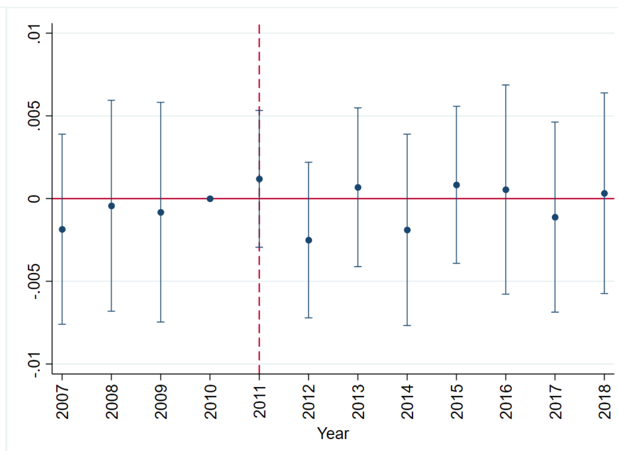
(a) Log Sales



(b) Log Employment



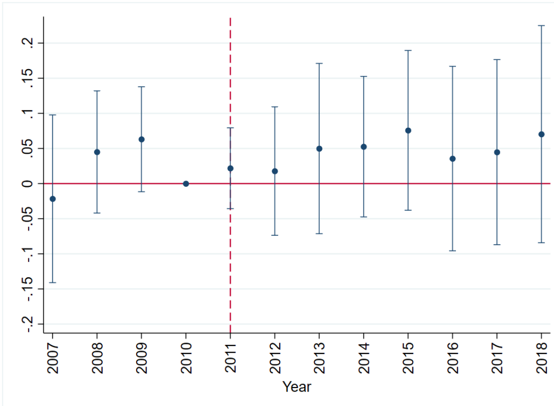
(c) Investment



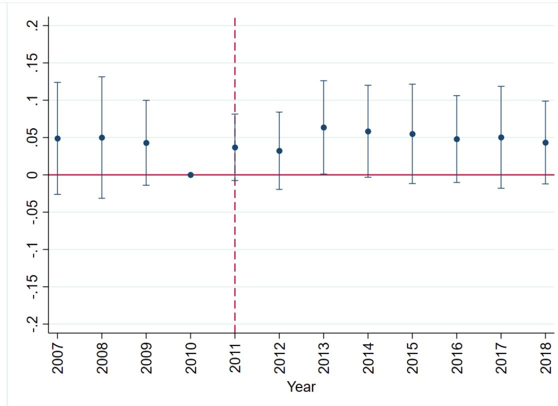
(d) Profit

Note: This figure plots the coefficients of difference-in-differences estimation. Four panels correspond to (a) log sales, (b) log number of employees, (c) capital expenditure divided by the number of employees, and (d) ordinary income divided by asset. The whiskers indicate the 95% confidence intervals based on the clustering in the 2-digit industry code and prefecture code, while the dots indicate the point estimates. The red vertical dotted line represents the year when the earthquake occurred.

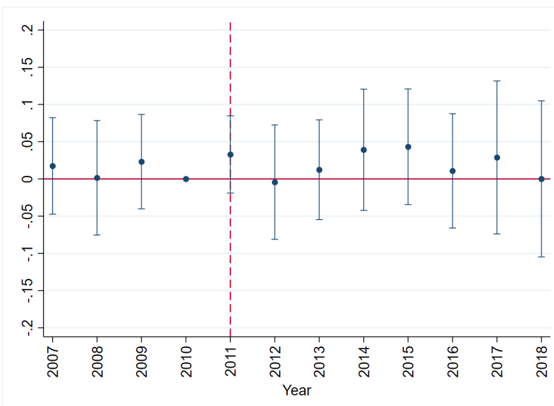
Figure B.2. The Impacts on Firm Performance (Productivity)



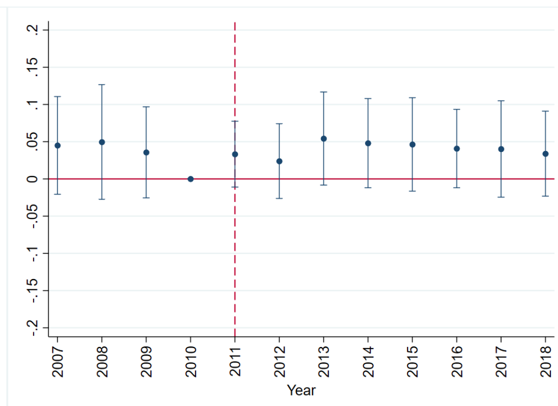
(a) ACF Productivity



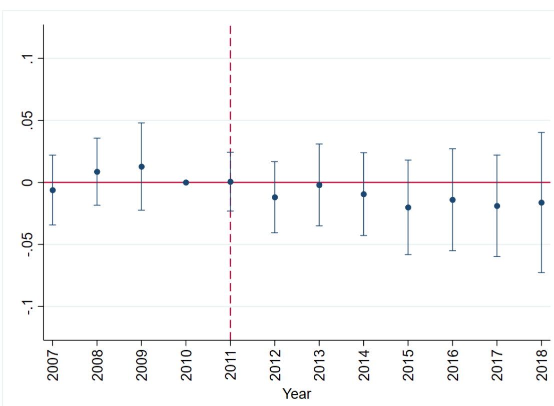
(b) LP Productivity



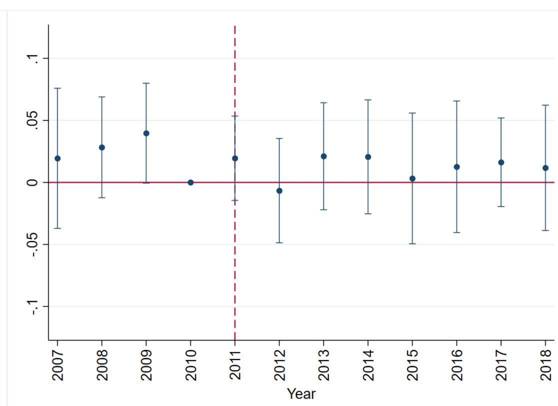
(c) OP Productivity



(d) Wooldridge Productivity



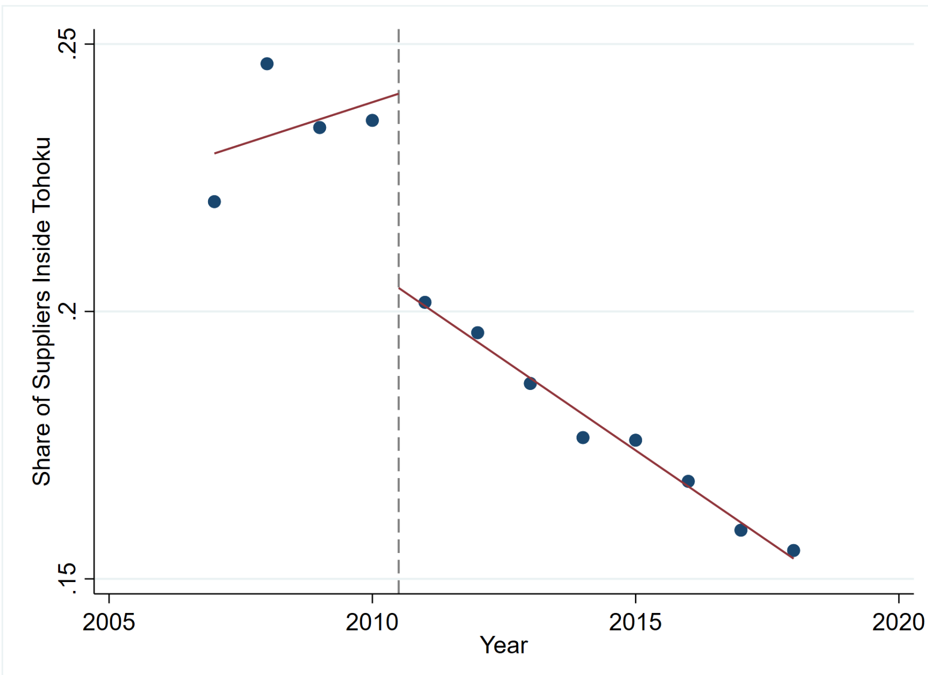
(e) Labor Productivity (Sales per worker)



(f) Labor Productivity (VA per worker)

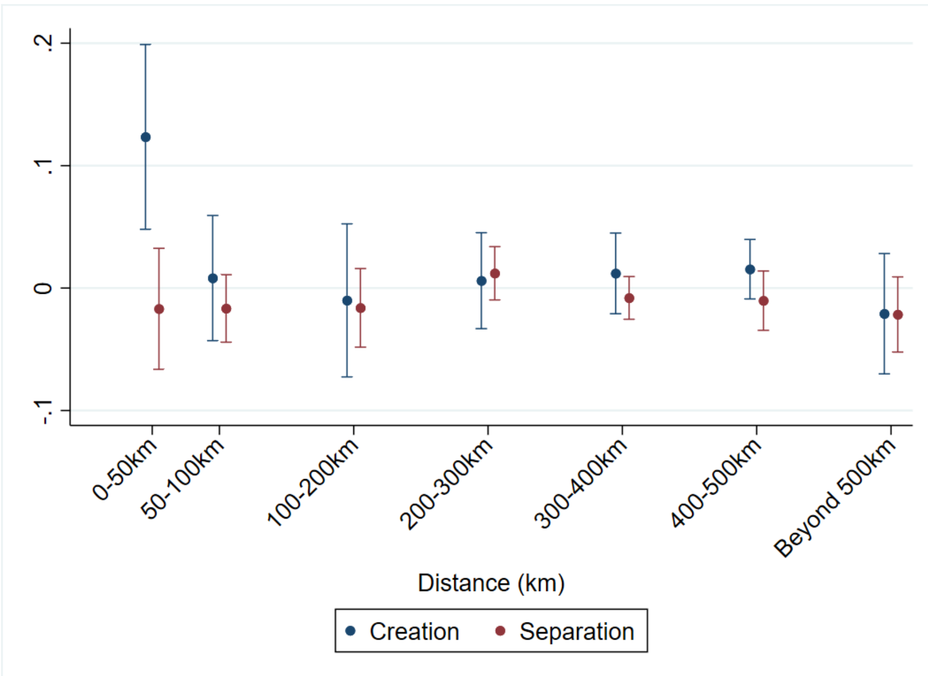
Note: This figure plots the coefficients of difference-in-differences estimation. Four panels correspond to (a) productivity estimated following the method of Ackerberg, Caves, and Frazer (2015), (b) productivity estimated following Levinsohn and Petrin (2003), (c) productivity estimated following Olley and Pakes (1996), (d) productivity estimated following the method of Wooldridge (2009), (e) labor productivity measured as sales divided by the number of employees, and (f) labor productivity measured as value added divided by the number of employees. The whiskers indicate the 95% confidence intervals based on the clustering in the 2-digit industry code and prefecture code, while the dots indicate the point estimates. The red vertical dotted line represents the year when the earthquake occurred.

Figure B.3. Share of Suppliers Inside the Disaster Area



Note: This figure focuses on buyer firms located outside the disaster area that had a supplier located inside the disaster area before 2011, and shows their unweighted share of suppliers located inside the disaster area. The share is defined as the number of suppliers inside the disaster area divided by the total number of suppliers across the whole of Japan.

Figure B.4. Log Number of New and Dropped Suppliers Within Distance Bands



Note: This figure plots the coefficients of difference-in-differences estimation with the log numbers of new and dropped suppliers within distance bands as outcomes. Excluding the disaster area, we split the rest of Japan into seven distance bands: 0–50 km, 50–100 km, 100–200 km, 200–300 km, 300–400 km, 400–500 km, and farther than 500 km from firms' headquarters. The whiskers indicate the 95% confidence intervals based on the clustering in the 2-digit industry code and prefecture code, and the dots indicate the point estimates of coefficients. The red ones correspond to the log number of new suppliers, while the blue ones correspond to the log number of dropped suppliers.