The London School of Economics and Political Science

Essays in Applied Microeconomics

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A thesis submitted to the Department of Economics
for the degree of Doctor of Philosophy.

Declaration

I certify that the thesis I have presented for examination for the Ph.D. degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I confirm that Chapters 1 and 3 are co-authored with Takafumi Suzuki and that Chapter 2 is co-authored with Nick Bloom, Charlotte Meng, Paul Mizen, Rebecca Riley, Tatsuro Senga, and John Van Reenen.

I declare that my thesis consists of approximately 28000 words.

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Abstract

This thesis consists of three chapters on trade and organizational economics. The first chapter examines the impact of the 2011 Great East Japan Earthquake on firm performance and supplier relationships. Using Japanese buyer-supplier linkage data and a difference-in-differences empirical strategy, this chapter focuses on buyer firms outside the disaster area and compares those with and without suppliers in the disaster area. On average, treated firms were not differentially hurt by the earthquake. Nonetheless, buyers in long-term relationships with suppliers in the disaster area suffered significant sales losses and struggled to replace their old suppliers. Moreover, the results show that treated firms disproportionately accumulated new suppliers closer to their headquarters. Using seismological data, it is shown that this nearshoring was not due to information update on earthquake risk and suggested it could be due to firms prioritizing supply chain resiliency. The second chapter investigates supply chain dynamics, exploiting panel data on buyer-supplier linkages in Japan. First, we provide evidence of substantial supply chain churning over time, even after excluding firm exits from the market. Second, we find that productivity positive assortative matching between firms exists: Firms are more likely to keep trading with more productive firms and instead stop trading with less productive ones. Lastly, we build a theoretical framework to rationalize these findings. Both supplier and customer firms are heterogeneous and choose their trading partners with a many-to-many matching framework. We derive the implications for supply chain formation and restructuring in response to productivity shocks. The third chapter studies management practices and forecasting ability among UK firms. We link a new UK management survey covering 8,000 firms to panel data on productivity in manufacturing and services. We find that better managed firms make more accurate micro and macro forecasts, even after controlling for their size, age, industry and many other factors. We also show better managed firms appear aware that their forecasts are more accurate, with lower subjective uncertainty around central values. These stylized facts suggest that one reason for the superior performance of better managed firms is that they knowingly make more accurate forecasts, enabling them to make superior operational and strategic choices.

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Chapter 1

Do Supply Chain Disruptions Harm Firm Performance? Evidence from Japan

1.1 Introduction

There have been a number of major supply chain disruptions in recent years such as the Ukraine invasion, Trump's trade wars, Brexit, COVID and extreme weather events linked to 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 and financial statements. 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, we document that the mean effect masks significant heterogeneity. In particular, for a sub-group of the treated who had a large fraction of long-term suppliers (i.e., those they had been trading with for several years) inside the earthquake zone there was a significant negative effect on sales and the ability to replace the suppliers with new ones outside the zone. Other treated firms with shorter relationships did not suffer significant damage to their performance. This is likely to be because the longer-term contracts were more relational and harder to replace.

In terms of the number of suppliers, 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. This happened for both sub-groups of treated firms but was weaker for those firms who relied more on long-term relational contracts. 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 findings show that treated firms' new suppliers are disproportionately close to their headquarters after the earthquake. A possible explanation is that these nearby areas were seismologically safer areas (i.e., firms are avoiding suppliers in areas where objective earthquake risk is high). Merging the seismological data with the firm-level buyer-supplier linkage data, we found that there is *no* clear pattern in supplier selection with respect to seismological risk. Rather, a combination of factors should have caused treated firms to put greater weight on geographical proximity. They could include that firms prioritized benefits of monitoring and acquiring information of suppliers' activities and that firms searched for alternative suppliers in hurry and then built up relational capital with them. Both cases would result in *nearshoring* that we have found. We find suggestive evidence that firms built up relational capital with nearby suppliers after the Great East Japan Earthquake.

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

[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."

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[3], European Chips Act[4], Japan's Economic Security Promotion Act[5]). 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 study. They use the same TSR data during 2010–2012 and find significant negative effect of the Great East Japan Earthquake on firm sales.

Our study differs from theirs in two important ways. First, we use the updated information for firm responses. As a feature of the survey, some firms provide responses in later years; we exploit those late responses to replace missing values in the original survey year. As we describe in the following sections, this led to the substantial reduction in the number of missing values compared to the dataset used in Carvalho et al. (2021). By exploiting the updated information, we find that treated firms' sales were not differentially hurt by the earthquake, as opposed to their findings. We explain in detail how this difference arises in section 4. Our replication exercises further confirm our results. Second, we examine the dynamic adjustment of supply chains, whereas they take the network as given. This analysis is feasible in our study because we use the buyer-supplier linkage data during 2007–2018, while they use the information on the supply chains only in 2010. As shown in section 4, we find that firms substantially replaced their suppliers since the earthquake. Moreover, we find that the effects were heterogeneous depending on the type of the supplier relationships that were affected by the disaster.

Second, it contributes to the literature on supply chains. Recent papers have investigated

[3]Source: White House (2022).
[4]Source: European Commission (2022).
[5]Source: Cabinet Office (2022).

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 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 chapter is structured as follows. Section 2 provides background information on the Great East Japan Earthquake. Section 3 describes the dataset 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.

1.2 The Great East Japan Earthquake

1.2.1 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%.[6] This share makes sense given that the population of the four prefectures makes up 5.5% of Japan's overall population (as of 2010).[7] 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.[8] These numbers are roughly proportional in size to the prefectures' share of the national GDP. Third, Figure 1.A1 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.

1.2.2 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.[9] 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 areas of the Tohoku region. As of May 2012, it was recorded that 15,859 people were killed,

[6] Cabinet Office, Government of Japan

[7] Cabinet Office, Government of Japan

[8] 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

[9] Source: U.S. Geological Survey

and 3,021 people were listed as missing due to the disaster.[10] 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.[11] 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 1.1 Panel (a) shows the geographical distribution of casualties, and Panel (b) shows damaged buildings in each municipality.[12] 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.[13]

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.[14] 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.[15] 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 severe damage on firms located inside the disaster area. Economic Census shows that the

[10] Cabinet Office, Government of Japan

[11] Cabinet Office, Government of Japan

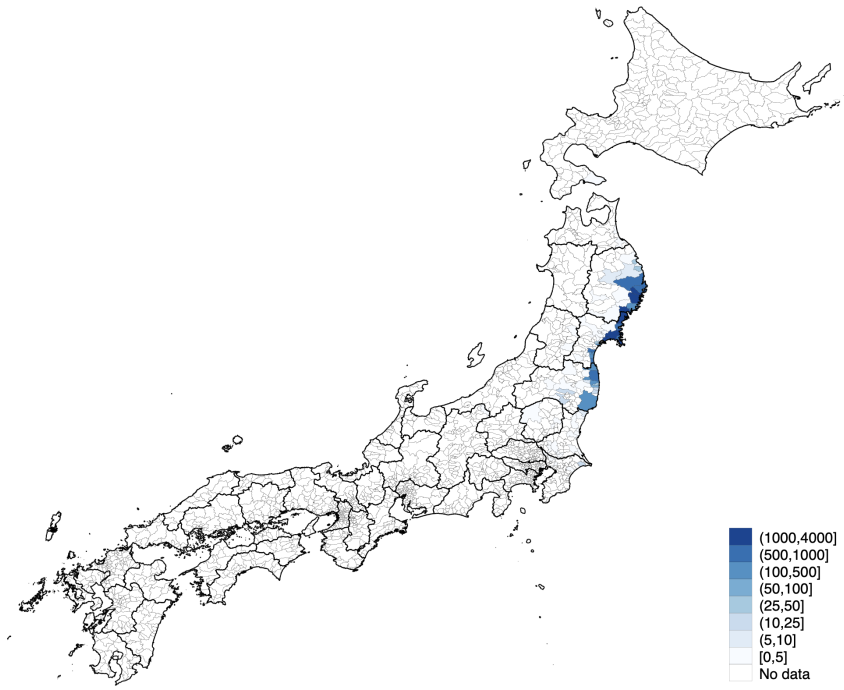
[12] Appendix Figure 1.A3 depicts the size of other measures that highlight the damage of the disaster.

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

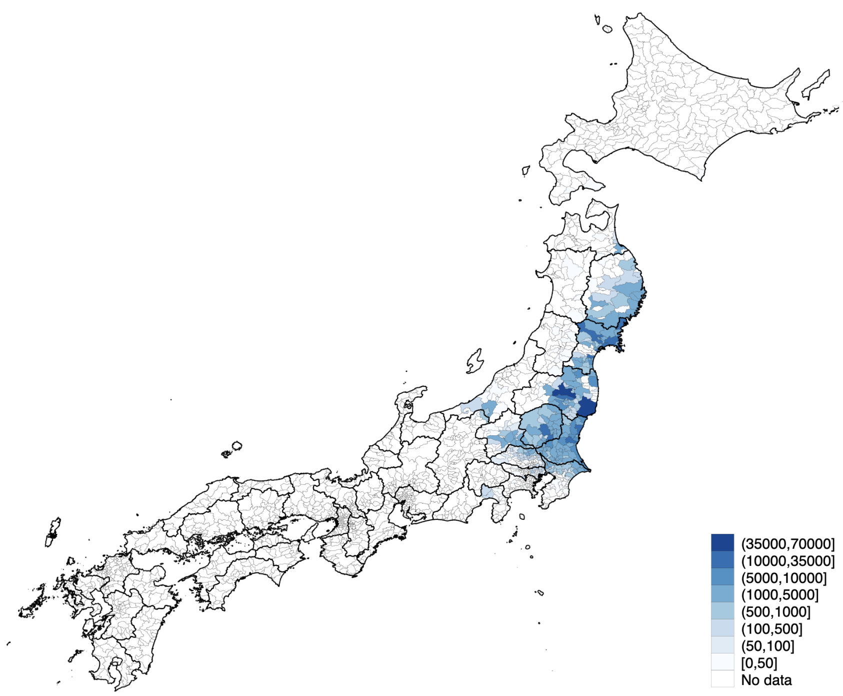
[14] The fiscal year in Japan begins in April and ends in March. As the earthquake occurred at the end of the fiscal year, the economic indicators in FY2010 barely reflect the impact. Therefore, we focus on the information in FY2011.

[15] Cabinet Office, Government of Japan.

Figure 1.1. 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.

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%.

1.3 Data

1.3.1 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 observe 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.

1.3.2 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. The total number of observations is around 4.5 million, which indicates that there were approximately 0.35 million observations for each year. The unique number of firms in the dataset is 565,529.

Table 2.1 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 35 employees, 6 suppliers and 5 customers. The maximum number of suppliers is 10,106, and that of customers is 4,940. This confirms that we capture domestic buyer-supplier linkages well beyond the cutoff.

Table 1.1. Summary Statistics

	# of obs	Mean	Median	SD	Max	Min
Firm sales	4,324,047	1626672.631	191500	41001039.418	2.5745e+10	1
Firm age	4,236,276	32.040	31	16.981	141	0
Firm size	4,489,022	35.390	8	244.683	62,000	1
Total # of links	4,514,650	10.206	6	24.467	10,110	1
# of suppliers	4,514,650	5.607	3	17.085	10,106	1
# of customers	4,514,650	4.599	2	14.313	4,940	0

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

1.4 Empirical Results

1.4.1 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.

1.4.2 The Impact on Firm Performance

1.4.2.1 Main Findings

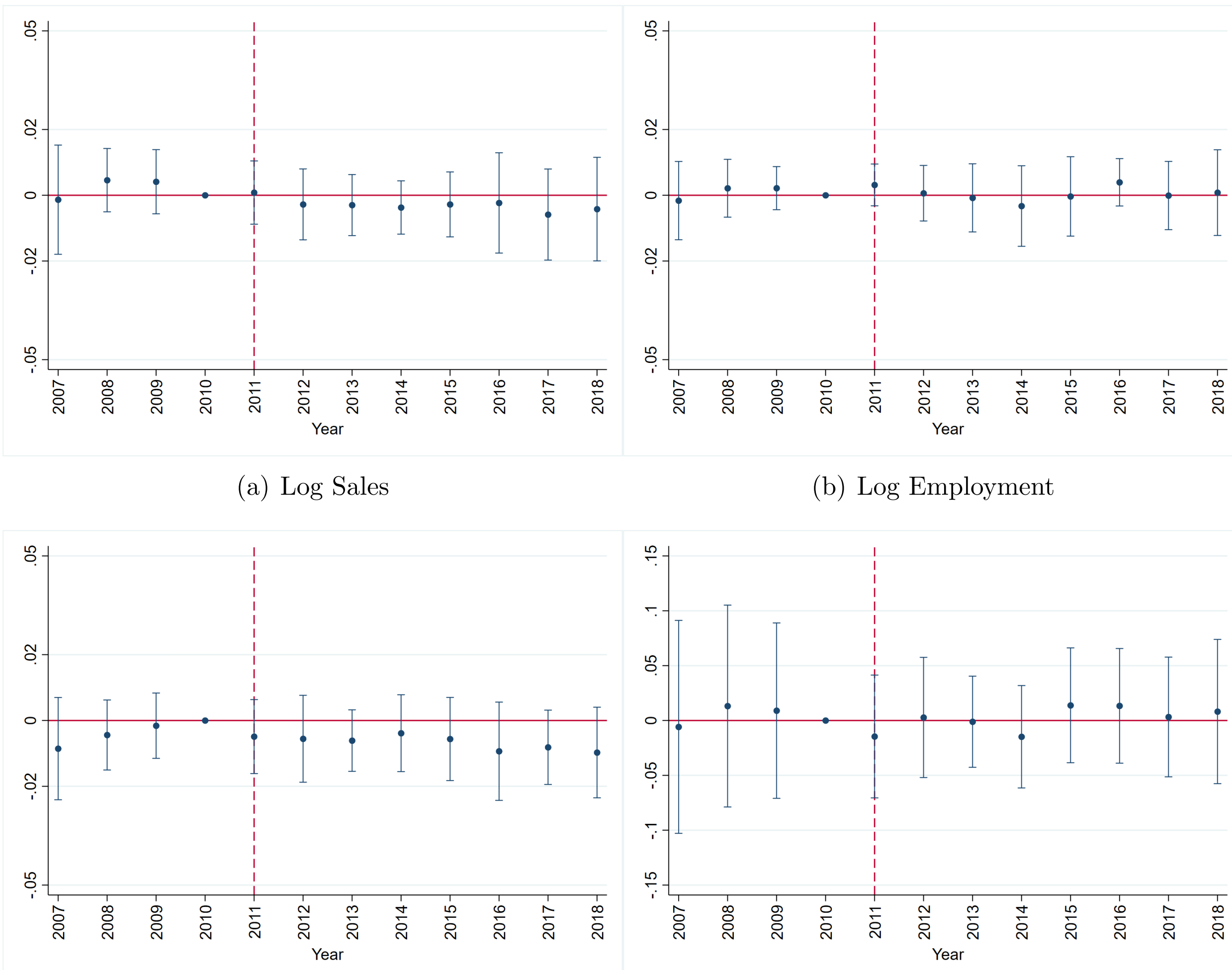
We begin by investigating the impact of the disaster on firm performance indicators. The disaster caused damage to the economic activities inside the disaster area and the rest of the country. The question here is whether the disaster had differential effects between the treatment and control groups. 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 1.2 then shows the results. Panel (a) uses log total sales as the outcome, Panel (b) log number of employees, Panel (c) labor productivity (defined as total sales divided by the number of employees), and Panel (d) productivity estimated following the method of Ackerberg et al. (2015).

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.

The result of Panel (a) is in stark 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. This is because we exploit the updated information in our dataset compared to theirs, by using the late responses by firms. As the feature of the firm-level survey, some firms responded to the survey in later years, which is not unique to the TSR data but also the case for similar firm-level data including Orbis. For example, a firm could respond in a lagged manner (e.g., in 2012) to the survey that asks the information of 2011. In that case, we originally have missing values in the survey of 2011, but many of them could be replaced with non-missing values by exploiting later survey responses (made in 2012 or later). This is what we do to construct our dataset. In contrast, Carvalho et al. (2021) only use the responses made each year and keep those missing values without replacements. By using the data until 2018, we reduce the number of missing values by about 15% compared to their dataset between 2010 and 2012.

With the larger number of observations for each survey year, we find that the earthquake did not differentially damage treated firms' performance compared to similar firms in the control group. We further confirm this by conducting two replication exercises. This is

Figure 1.2. The Impacts on Firm Performance



(a) Log Sales

(b) Log Employment

(c) Labor Productivity

(d) ACF Productivity

Note: This figure plots the coefficients of difference-in-differences estimation. Four panels correspond to (a) log sales, (b) log number of employees, (c) labor productivity measures as sales divided by the number of employees, and (d) productivity estimated following the method of Ackerberg, Caves, and Frazer (2015). 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.

summarized in Figure 1.B1. First, we use the data from 2010 and 2012 and do not exploit the late responses by firms. Then, we obtain a very similar estimate with that of Carvalho et al. (2021), which is negative and statistically significant. Second, we extend the data to cover from 2007 to 2018 and conduct the estimation without exploiting the late responses. Then, again, we obtain an estimate close to theirs. However, when we exploit the late responses with the 12-year panel data, we obtain a statistically insignificant coefficient as described above. More detailed information on our replication exercises can be found in Appendix B.

1.4.2.2 Robustness checks

To further confirm that treated firms were not differentially hurt by the earthquake, we have conducted several robustness checks. First, we deal with the concern of the potential impact of the disaster on the control group. Firms in the control group could suffer partial impact from the disaster through supply chains even if they did not have direct supplier located inside the disaster area. To this end, we calculate the steps of transactions by which they reach a supplier located inside the disaster area. We refer to the number of steps as degree, so firms with degree one are the treated firms. Control firms with lower degree are more likely to have partial impact through the supply chains. We conduct the similar estimation exercise by excluding firms in the control group with degree two to four. As shown in Figure 1.A4, the results are consistent with what we find without imposing the exclusion restriction. Therefore, we can judge that the potential impact on control firms is not a major concern.

Second, we deal with the concern of sample bias. One source of bias is the survival of firms. If there are many firms that exited during the sample period, the regression results with only surviving firms could be biased. We can deny this concern as there were only a few firm exits during the sample period. Every sample year, about 4–5% or even lower share of firms exited from the market. The rate was almost stable across the sample period, so this should not have a huge influence on the results. On top of this, we have conducted a robustness check by replacing sales after firm exit with 0 and rerunning the same regression. Figure 1.A5 shows the similar results as before. Therefore, we can exclude the concern of the survival bias. Another source of the bias is firm relocation from inside to outside of the disaster area. Again, we can deny it as this is a minor case. Only about 30–40 firms that located inside the disaster area before 2011 moved to the rest of Japan after that. This means that only about 0.02% of suppliers relocated between two zones.

Third, Figure 1.A6 shows the results when we restrict the sample to firms in the manufacturing sector only. There is no significant pre-trend. Once again, the four outcomes do not have significant coefficients in either the short or long run in the aftermath of the earthquake. Fourth, Figure 1.A7 shows the results for productivity measures that are demeaned within industry. Again, we make two key observations. There is no significant pre-trend for both outcomes. Also, the coefficients for 2011–2018 are not significant. Fifth, we have also conducted propensity score matching to ensure that firms in treatment and control groups become similar. As shown in Figure 1.C1, estimation results after matching are consistent with our findings before matching. 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 if treated firms find 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.

1.4.3 Restructuring of Supply Chains

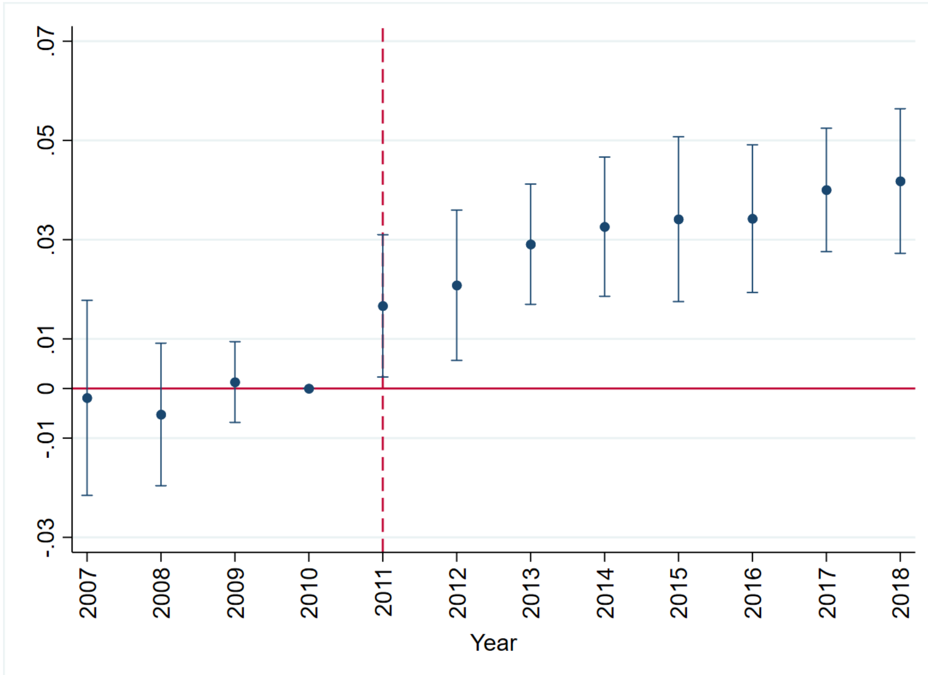
1.4.3.1 Numbers of Suppliers: Outside the Disaster Area vs Entire Country

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 outcomes, Y_{it}, we use (i) the number of suppliers located outside the disaster area and (ii) the total number of suppliers in the whole of Japan. Comparing these two outcomes, we can investigate whether treated firms were able to maintain their total number of suppliers across Japan or not and how they achieved that in face of the loss of suppliers inside the disaster area. If firms did not have new suppliers located outside the disaster area, the total number of suppliers naturally declined.

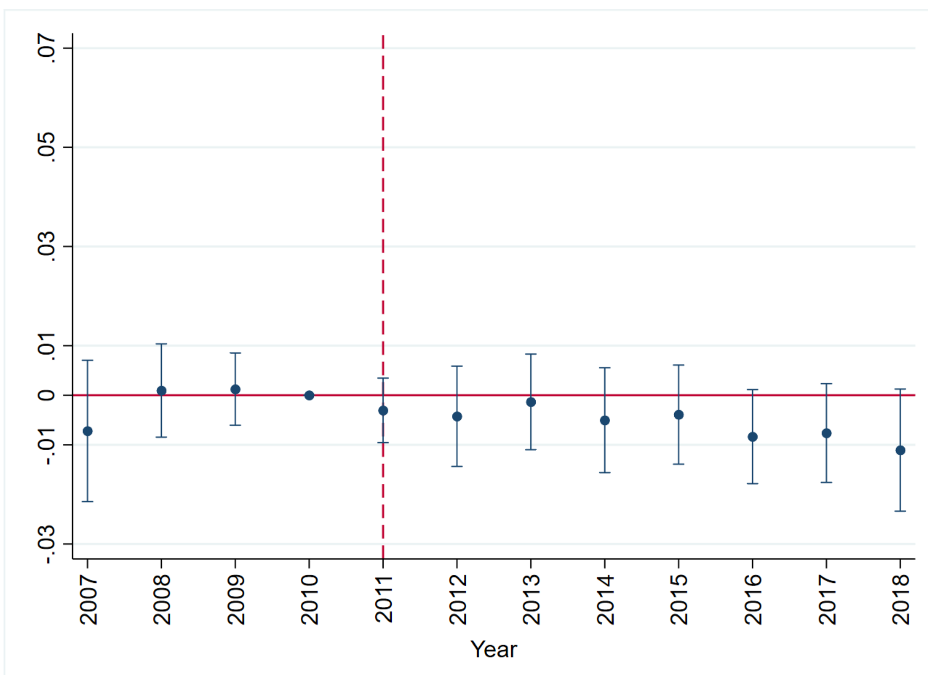
Figure 1.3 shows the results. Panel (a) displays the results for the number of suppliers located outside the disaster area. The coefficients for 2011–2018 are significant and positive. Also, the coefficients persistently increase from 2011 to 2018. Thus, treated firms did not return to suppliers located inside the disaster area, and they continued adding new suppliers located outside the disaster area after the earthquake. This implies substantial churning of their supply chains, particularly diverting away from the disaster area.

Conversely, Panel (b) displays the total number of suppliers. The coefficients for all years are insignificant although the coefficients since 2011 are slightly negative. Moreover, the total number of suppliers did not significantly change between the treatment and control groups, which suggests that the treated firms managed to maintain their total number of suppliers despite the disruptions caused by the earthquake.

Figure 1.3. Log Number of Suppliers



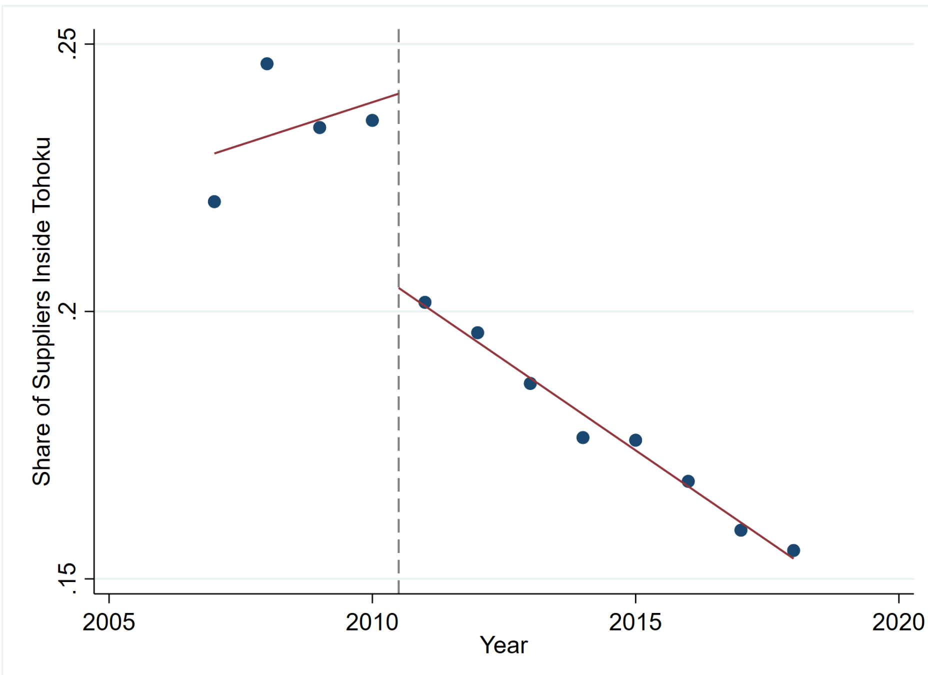
(a) The Number of Suppliers Outside



(b) Total Number of Suppliers

Note: These figures plot the coefficients of difference-in-differences estimation with (a) the log number of suppliers outside the disaster area, and (b) the log total number of suppliers as outcomes. 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 1.4. 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.

1.4.3.2 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 1.4 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.

In the next section, we conduct heterogeneity analyses to explore the relationship between the substantial restructuring of the supply chains and the mitigation of the damage caused by the disaster. In particular, we intend to test whether treated firms that could switch to alternative suppliers were not damaged and whether those firms that could not find alternative suppliers suffered significant sales losses.

1.5 Heterogeneity Analyses: Duration of Relationships

We conduct heterogeneity analyses focusing on the duration of relationships with suppliers inside the disaster area before the earthquake. This is a proxy of the importance of suppliers, or the specificity of product that they supply. To that end, our exercise explained here is in the same spirit with Giannetti et al. (2011) and Barrot and Sauvagnat (2016) that use the classification of differentiated products proposed by Rauch (1999). We divide the sample of treated firm into those in short- and long-term relationships with suppliers located inside the disaster area.

We first calculate treated firms' average duration of relationships with suppliers between 2007 and 2010.[16] Then, we divide the treatment group into firms with the duration of the relationships above and below median. We continue to impose the same set of sample restrictions on buyer firms: (i) located outside the disaster area; (ii) had at least one cross-prefectural transaction; and (iii) have not supplied inputs to the disaster area before 2011.

We conduct a difference-in-differences estimation and separately estimate coefficients for two groups of treated firms defined above. We run the following regression:

$$\begin{aligned} Y_{it} &= \beta_1 D_i \times After_t \times Short_i + \beta_2 D_i \times After_t \times Long_i \\ &\quad + \beta_3 After_t \times Short_i + \beta_4 After_t \times Long_i \\ &\quad + \gamma_1 X_i^{2010} + \gamma_2 X_i^{2010} \times After_t + \tau_{jkt} + \epsilon_{it}, \end{aligned} \tag{2}$$

[16] The median is three years.

where D_i is a dummy that takes the value of 1 if a firm i had a supplier inside Tohoku before 2011, and $After_t$ is a dummy that takes the value of 1 for years since 2011 and 0 otherwise. $Short_i$ is a dummy that takes the value of 1 if a firm was in a short-term relationship with suppliers inside the disaster area, whereas $Long_i$ is a dummy that takes the value of 1 if a firm was in a long-term relationship with suppliers inside the disaster area. X_i^{2010} refers to firm covariates including the number of suppliers, the distance to the disaster area, firm age as of 2010. We also include prefecture-4-digit industry-year fixed effects, τ_{jkt}. The standard errors are two-way clustered with prefecture and 2-digit industry.

For the outcomes, Y_{it}, we use (i) firm sales, (ii) the number of suppliers located outside the disaster area and (iii) the total number of suppliers in the whole of Japan. The key parameters to estimate are β_1 and β_2. The coefficient β_1 corresponds to firms that had a short-term relationship with suppliers located inside the disaster area from 2007–2010, whereas the coefficient β_2 corresponds to firms that had a long-term relationship.

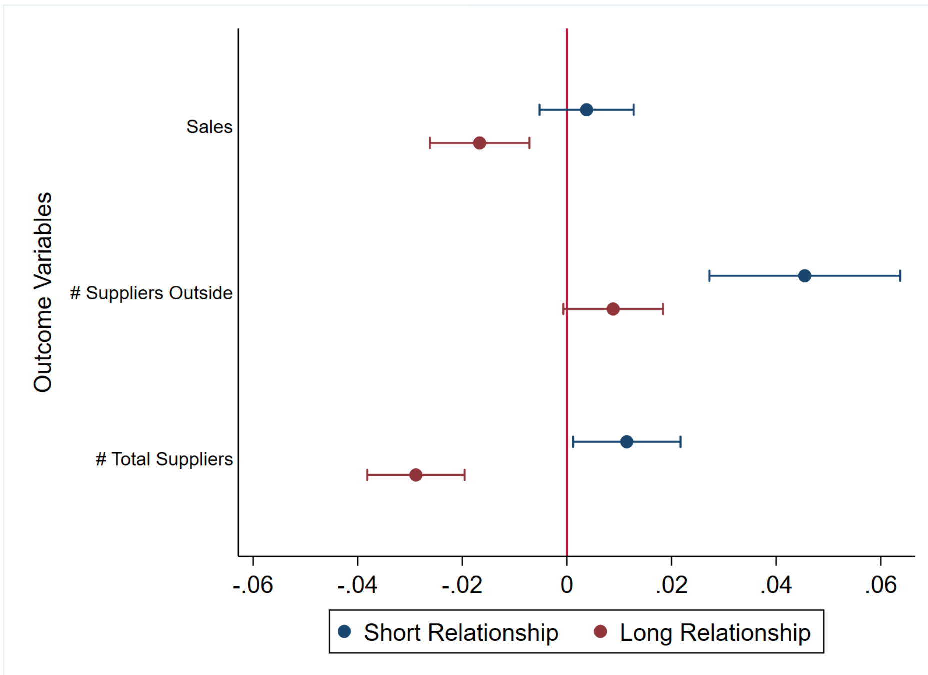
Figure 1.5 shows the results of difference-in-differences estimation. Each of the three variables on the y axis is the outcome of each regression. The red dots and whiskers correspond to firms in a long-term relationship with suppliers located in the disaster area between 2007 and 2010, whereas the blue ones correspond to firms in a short-term relationship.

The results are as follows. First, we find that firms in a long-term relationship with suppliers located inside the disaster area significantly suffered sales losses, wheres those in a short-term relationship did not. This implies that the effects on firm sales are heterogeneous depending on the duration of relationship. As we think of the duration as a proxy of the importance of suppliers, we interpret that firms incurred more significant damage to their sales when they had important suppliers inside the disaster area.

To look into the underlying factor of the heterogeneity, we also analyze the impact on firms' supplier relationships. Second, we focus on the outcome as the number of suppliers located outside the disaster area.

We obtain a positive and significant estimate of β_1 and an insignificant estimate of β_2. This implies that firms in a short-term relationship with suppliers inside significantly increased the alternative suppliers located outside. However, firms in a long-term relationship with suppliers inside could not find alternative suppliers outside the disaster area. The heterogeneity in the ability to quickly replace their lost suppliers that depends on the duration of relationship further resulted in the differential impact on firm sales. Also, as the consequence of heterogeneous impact on the increase in the number of suppliers located outside, the total number of suppliers for firms in a long-term relationship significantly decreased after the disaster. This is again in contrast to firms in a short-term relationship: The total number suppliers did not decrease but rather slightly increased.

Figure 1.5. Heterogeneity Based on Duration



Note: These figures plot the coefficients of difference-in-differences estimation with (a) log firm sales, (b) log number of suppliers outside the disaster area, and (c) log total number of suppliers as outcomes. 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 ones correspond to firms in a long-term relationship with suppliers located in the disaster area between 2007 and 2010, whereas the blue ones correspond to firms in a short-term relationship.

Taken together, these results highlight the importance of swift adjustment of supply chains for firms' resilience against disruptions. On average, treated firms' sales were not differentially hurt by the earthquake. Nonetheless, the effects were heterogeneous depending on the duration of relationships. Firms that had long-term relationships with suppliers inside the disaster area suffered more significant sales losses since they could not find alternative suppliers. In contrast, those firms in shorter relationships that could quickly switch to alternative suppliers located outside the disaster area after 2011 succeeded in mitigating the negative propagation impact of the disaster.

As a robustness check, we conduct subsample regressions of dynamic difference-in-differences estimation. We divide the sample into two groups based on the median duration: The treated firms who had a relationship with suppliers inside for longer than the median time, and the rest of buyer firms that had shorter relationships.

Figure 1.A8 plots the coefficients separately for below- and above-median subsamples. From Panel (a), we find that buyer firms that had shorter relationships did not suffer sales losses due to the earthquake. However, Panel (b) shows that buyer firms that had longer relationships with suppliers inside the disaster area had significant damage to their sales due to the earthquake. These suggest that firms that were more dependent on disaster-hit suppliers had more significant damage to their performance.

Next, we examine the heterogeneity in the ability to find alternative suppliers to shed light on the mechanism. Figures 1.A9 and 1.A10 plots the coefficients of difference-in-differences estimation separately for below- and above-median subsamples. From Panel (a), we find that buyer firms that had shorter relationships with suppliers inside the disaster area significantly increased the number of suppliers outside by replacing lost suppliers with new ones. Moreover, it shows that those firms gradually increased the number of suppliers located outside the disaster area. Panel (b) suggests that buyer firms that were more dependent stuck with old suppliers inside the disaster area and consequentially had larger damage to their performance. In Figure 1.A10, Panel (a) shows that the total number of suppliers remained broadly unchanged for buyer firms that had shorter relationships, whereas Panel (b) shows that buyer firms that had longer relationships with suppliers inside the disaster area significantly lost suppliers after the earthquake.

1.6 Localization of Supply Chains

1.6.1 Number of Suppliers Within Distance Bands

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:

$$Y_{idt} = \beta D_i \times After_t + X_i^{2010}\gamma + \eta_i + \tau_{jkt} + \epsilon_{idt}, \tag{3}$$

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 $After_t$ 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.

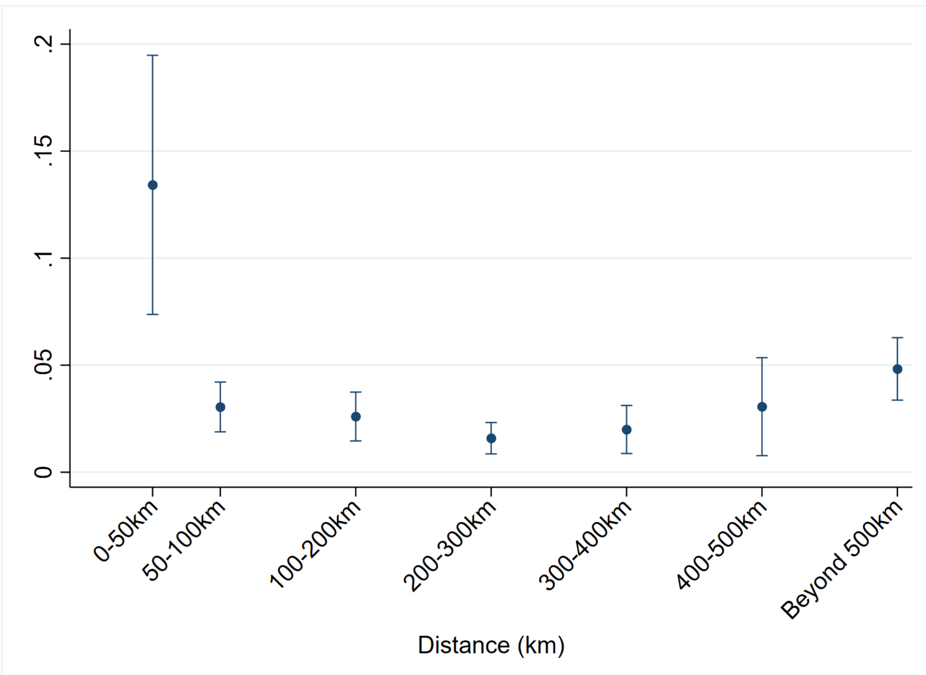
Figure 1.6 shows the estimated results for each distance band. The results are as follows. First, all of the coefficients are significant across distance bands, indicating that the treated firms had more suppliers everywhere compared to similar control firms. Second, and more strikingly, the estimated coefficient is the largest for the closest range, being approximately three times larger than other coefficients. After the disaster, the treated firms had approximately 13.4% 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 distribution. The specification is as before:

$$Y_{idt} = \sum_{t=-3}^{8} \beta_t D_i T_t + \sum_{t=-3}^{8} \gamma_t X_i^{2010} T_t + \eta_i + \tau_{jkt} + \epsilon_{idt}, \tag{4}$$

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 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}.

Figure 1.6. 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.

The standard errors are two-way clustered.

In Figures 1.A11 and 1.A12, we plot the estimated coefficients with the dynamic difference-in-differences estimation. The effect was largest in 2011 as we expect, but the effects persistently accumulated until the end of the sample period, i.e., 2018. In the closest distance band (i.e., 0–50 km from firms' headquarters), the effect on the number of suppliers was approximately 7.1% in 2011, rising to around 27.2% in 2018. Moreover, the mean of coefficients for 2011–2018 in the closest distance band is roughly 16.6%, which is consistent with what we find in Figure 1.6. These results confirm that treated firms had more suppliers across all distance bands, but also that these suppliers were disproportionately located within the closest distance band over time.

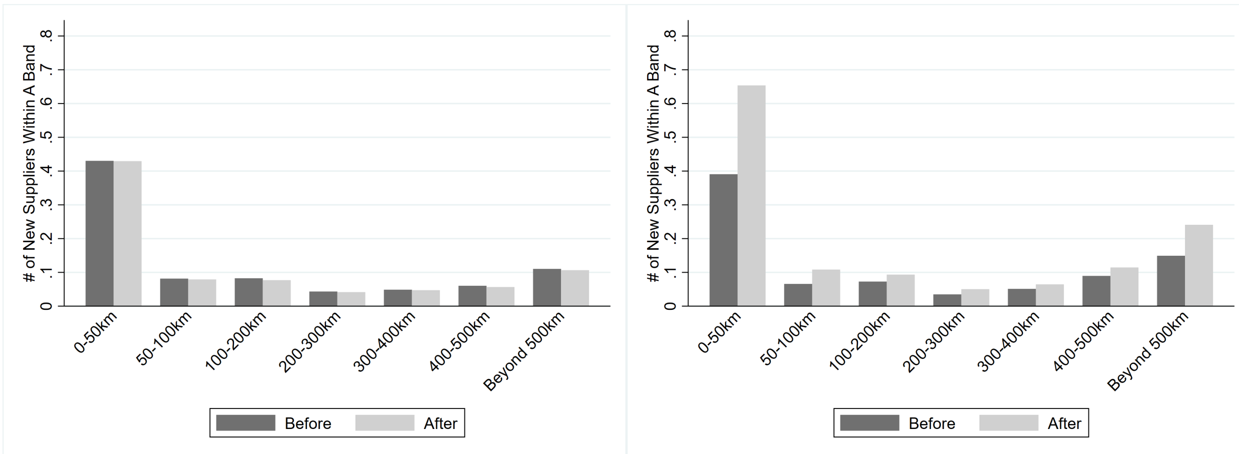
1.6.2 Numbers of New and Dropped Suppliers

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.

Figure 1.7 shows the spatial distributions of new suppliers separately for before and after the earthquake and for the treatment and control groups. In the control group, the distributions between pre- and post-earthquake periods are almost the same. The control firms naturally had more new suppliers nearby because of the existence of trade costs that are increasing in distance, but importantly they did not change their behaviors across two periods. For the treatment group, however, there is a striking increase in new suppliers within the closest band that is much larger than the increases observed in more distant locations. It should be noted that the results here do not control for firm characteristics (e.g., firm sales, size, age) but they suggest that the data apparently satisfy the identification assumption required for difference-in-differences estimation.

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

Figure 1.7. Numbers of New Suppliers: Control vs Treatment Groups



(a) Control Group (b) Treatment Group

Note: This figure plots the average numbers of new suppliers, separately for control and treatment groups. Excluding the disaster area, we split the rest of Japan into the distance bands from firms' headquarters: 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 dark grey bars show the averages for the pre-earthquake period during 2007–2010. The light grey bars show those for the post-earthquake period during 2011-2018.

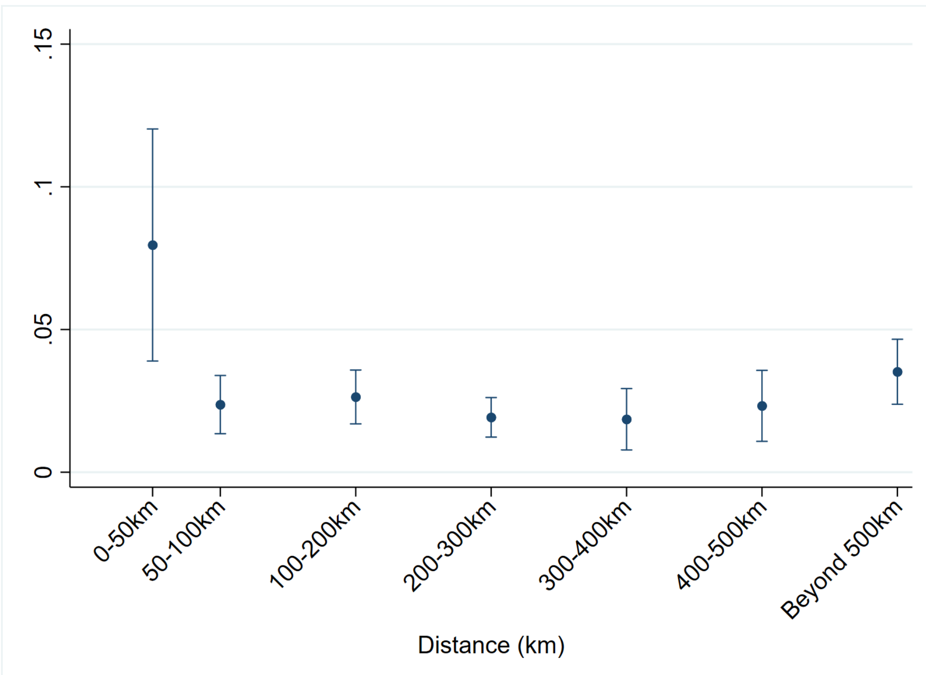
of suppliers has been affected by the earthquake. We modify the specification to be as follows:

$$Y_{idt} = \beta D_i \times After_t + \gamma X_i^{2010} + \sum_d \lambda_d Supp_{id}^{2010} + \eta_i + \tau_{jkt} + \epsilon_{idt}, \tag{5}$$

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.

First, we examine the impact on the log number of new suppliers in each distance band. Figure 1.8 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 8% more new suppliers within 50 km from their headquarters, compared to the control firms. This is

Figure 1.8. Log Number of New Suppliers Within Distance Bands

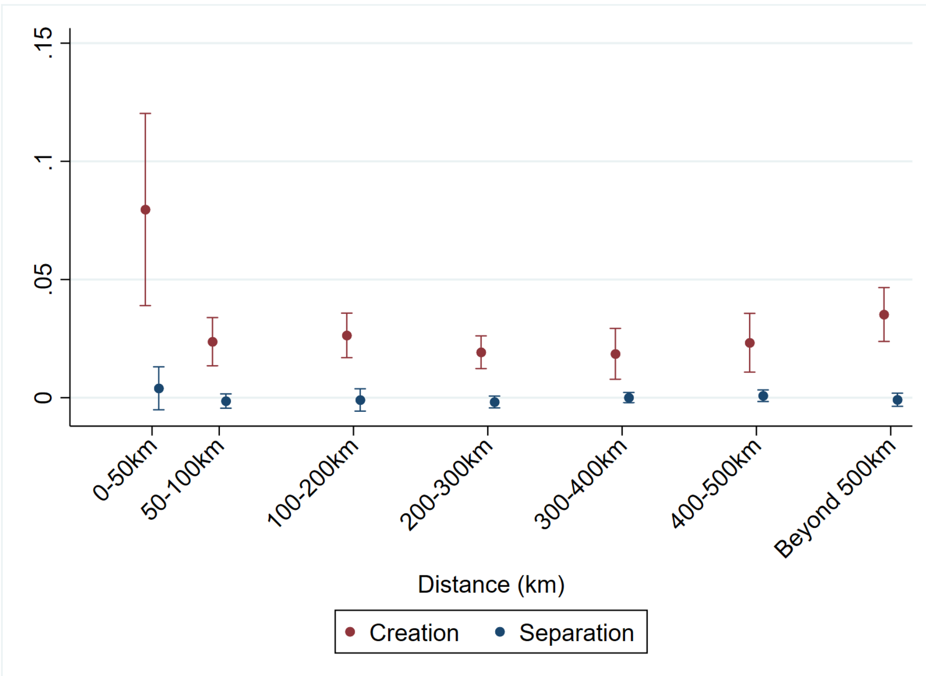


Note: This figure plots the coefficients of difference-in-differences estimation with the log numbers of new suppliers within distance bands as outcomes. Excluding the disaster area, we split the rest of Japan into seven distance bands: 0–50 km, 50–100 km, 100–200 km, 200–300 km, 300–400 km, 400–500 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.

the result for aggregating the post-earthquake period between 2011–2018.

Second, in Figure 1.9, 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.

Figure 1.9. 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.

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 as shown before. Moreover, the sizes of the coefficients are very small, ranging from 0.4% for the closest band (i.e., within 0–50 km) to 0.0% for 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.

Again, we additionally investigate the dynamics in the accumulation of suppliers over spatial distribution. First, in Figures 1.A13 and 1.A14, we plot the estimated coefficients for the log number of new suppliers. Panels (a)–(e) correspond to each distance band. There is no significant pre-trend across all distance bands. The graphs show that the effect was the largest in 2011 but that the effects persisted until 2018. In the closest distance band (i.e., 0–50 km from firms' headquarters), the effect was roughly 11.4% in 2011 and around 7.0% in 2018. Moreover, the mean of coefficients for 2011–2018 in the closest distance band is about 7.2%, which is in line with the effect found in Figure 1.6. These results confirm that treated firms had more suppliers across all distance bands but that suppliers were disproportionately concentrated nearby.

Second, in Figures 1.A15 and 1.A16, we plot the estimated coefficients for the log number of dropped suppliers. Once again, there is no significant pre-trend across all distance bands. The effects in the post-earthquake period are very small. In the closest distance band (i.e., 0–50 km from firms' headquarters), the effect in 2011 is -0.6% and insignificant. Furthermore, the mean of coefficients for 2011–2018 in the closest distance band is about 0.4%. This is consistent with what we found in Figure 1.9. These results also confirm that treated firms had more new suppliers across all distance bands disproportionately nearby but they dropped old suppliers evenly across space.

1.6.3 Robustness Checks

We also conduct three additional robustness checks. First, we examine the distance to suppliers. Given the set of suppliers, we calculated the median, maximum, minimum and standard deviation of the distances between buyer firms and their suppliers. Each panel in Figure 1.A17 shows the result for each outcome. There is no significant pre-trend. Overall, the four panels confirm that the distance to suppliers became smaller from 2011 onwards. The maximum and minimum distances decreased, which resulted in the decline in the median distance as well as the standard deviation of the distance. It should be noted that the effects are persistent over time, which is consistent with our earlier findings, i.e., the treated firms increased their number of new suppliers nearby and dropped old suppliers evenly across space after the earthquake.

Second, we study the regional share of suppliers. For buyer firms, we calculated the share of their suppliers located in the same prefecture. We also performed the same calculation for the share of suppliers located in the same region, which is a more aggregated geographical unit than a prefecture.[17] Figure 1.A18 depicts the results of the dynamic difference-in-differences estimation. Panel (a) shows the results for the same prefecture, and Panel (b)

[17] A region roughly consists of around six prefectures in Japan.

shows those for the same region. The share of suppliers in the same prefecture increased by around 2% in 2011 and persisted until 2018. The share of suppliers in the same region similarly increased, but the coefficients are not significant. These results are less pronounced than our findings on distance bands for two reasons: (1) a prefecture is a large geographical unit; and (2) we used the share as the outcome, whereas in the previous section, we used the log number of suppliers as the outcome.

Third, to investigate a potentially persistent change in the geography of supply chains due to the Great East Japan Earthquake, we construct a measure of concentration.

$$\text{Concentration}_{it} = \sum_j p_{ijt}^2, \tag{6}$$

where p_{ijt} is firm i's share of suppliers in a prefecture j in year t.[18] In the baseline, the average concentration of the treatment group is 0.17, while that of the control group is 0.39. The measure could mechanically increase when a firm loses a supplier and does not replace it by adding an alternative supplier. To eliminate such cases, we restrict the sample to those firms that lost at least one supplier inside the disaster area and added at least one supplier outside the disaster area between 2007–2010 and 2011–2014.

Figure 1.A19 plots the results of the dynamic difference-in-differences estimation while using the concentration measure defined in equation (6) as the outcome. There is no significant pre-trend. The coefficients become positive and significant after 2011 and show a positive trend between 2011 and 2018. The coefficient for 2011 is around 0.2, whereas that for 2018 reaches roughly 0.5. The mere 0.2 change in concentration measure could be a result of a change in prefecture-wise supplier share by more than 10% and should be interpreted as a major change.[19] This finding implies that the treated firms localized their supply chains. We obtained similar results without the sample restriction.

The results in sections 4.3 and 4.4 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.

[18] There are 47 prefectures in Japan.

[19] Suppose that a firm has its 40% of suppliers in Prefecture A, 20% in Prefecture B, 20% in Prefecture C, 10% in Prefecture D, and the remaining 10% in Prefecture E. This amounts to a concentration of 0.26. Then, also suppose that the firm restructures the supply chains to have 40% of suppliers in Prefecture A, 20% in Prefecture B, 20% in Prefecture C, and 20% in Prefecture D, and no more in Prefecture E. This leads to concentration of 0.28. The mere change in concentration of 0.02 is driven by moving 10% of suppliers away from a prefecture.

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.[20] 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. In the next section, we further explore the motive for treated firms' nearshoring.

1.7 Mechanism

1.7.1 Hypothesis: Information on Earthquake Risks

The results thus far show that the treated firms localized their supply chains after the disaster. They achieved this by taking on a disproportionate number of new suppliers nearby and dropping old suppliers evenly across space. In this subsection, we examine the underlying mechanism behind *nearshoring* by treated firms. A testable hypothesis is that firms selectively avoided the locations that were predicted to have a higher likelihood of major earthquakes. To examine this hypothesis, we exploit the seismological information provided by the National Research Institute for Earth Science and Disaster Prevention (NIED), which provides annual forecasts of earthquake hazard levels. We focus on the probability of an earthquake with a seismic intensity lower 6 in the next 30 years. An earthquake with a seismic intensity lower 6 is very large and rare. When such a powerful earthquake hits, people lose their balance and find it difficult to stand, and building structures may be destroyed or irreparably damaged.[21] The Great East Japan Earthquake, which was, as stated previously, the most powerful earthquake ever recorded in Japan, is categorized as having a seismic intensity of 7, placing it in the highest category.

Table 1.2 shows the forecast likelihoods of earthquakes' seismic intensity by quintile. At the 20th percentile, a location has a likelihood of 3.5% of experiencing an earthquake with a seismic intensity lower 6 in the next 30 years. At the 80th percentile, a location has a

[20] 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

[21] Source: Japan Meteorological Agency.

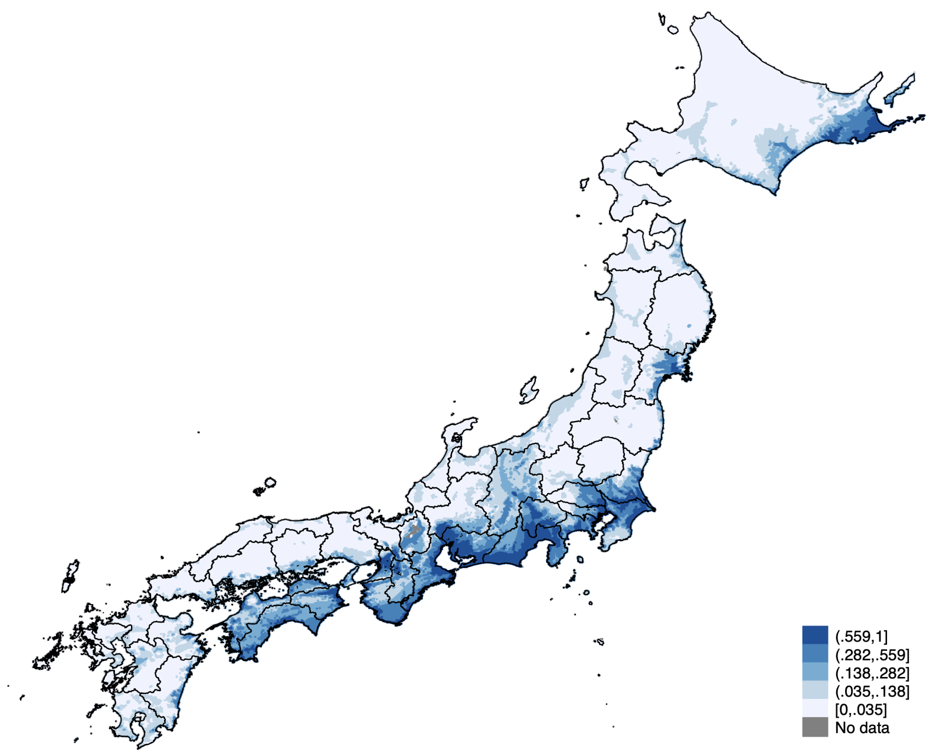
likelihood of 55.9% of experiencing an earthquake with a seismic intensity lower 6 in the next 30 years. We divide the locations into five bands using quintiles of hazard forecasts shown in Table 1.2 as thresholds. Figure 1.10 shows the spatial distribution of hazard forecasts. Different colors correspond to different quintile bands. Locations with higher hazard forecasts tend to be concentrated along Pacific coastal areas. They include top metropolitan areas (e.g., Tokyo, Osaka, and Nagoya). Therefore, in Japan, large cities tend to have a higher likelihood of experiencing major earthquakes.

Table 1.2. Hazard Forecast Quintiles of Seismic Intensity Lower 6

	p20	p40	p60	p80
Hazard Forecast	.035	.138	.282	.559

Source: The National Research Institute for Earth Science and Disaster Prevention (NIED).

Figure 1.10. Map of Hazard Forecasts: Seismic Intensity Lower 6



Note: This figure depicts the 2010 level of earthquake hazard forecasts of seismic intensity lower 6 in the next 30 years. Different colors correspond to different quintile bands.
Source: National Research Institute for Earth Science and Disaster Prevention (NIED).

We explore whether treated firms avoided locations that are more likely to have earthquakes with a seismic intensity lower 6 in the next 30 years. Excluding the disaster area, we divide the locations into five categories, each of which correspond to a quintile of the hazard forecasts shown in Table 1.2. We run the following difference-in-differences estimation:

$$\begin{aligned} Y_{iqt} \;=\; & \sum_{t=-3}^{8} \beta_t D_i T_t + \sum_{t=-3}^{8} \gamma_t X_i^{2010} \times T_t + \sum_{q} \sum_{t=-3}^{8} \lambda_{qt} Supp_{iq}^{2010} \times T_t \\ & + \sum_{t=-3}^{8} \delta_t Hazard_i^{2010} \times T_t + \sum_{t=-3}^{8} \theta_t SuppHazard_i^{2010} \times T_t \\ & + \sum_{r=1}^{10} \sum_{t=-3}^{8} \phi_t MEA_{ir}^{2010} \times T_t + \eta_i + \tau_{jkt} + \epsilon_{iqt}, \end{aligned} \tag{7}$$

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. The outcome, Y_{iqt}, is the log number of new suppliers within a quintile band q. $Supp_{iq}^{2010}$ is the number of suppliers in a quintile band q in 2010. As before, X_i^{2010} refers to firm covariates including firm size, measured as the number of employees, 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.

We additionally control for three new terms. $Hazard_i^{2010}$ is the level of hazard forecast made in 2010 for a location of firm i, and $SuppHazard_i^{2010}$ is the mean level of hazard forecasts made in 2010 across suppliers' locations. We control for these two variables because firms could locate themselves and pick their suppliers in locations with a lower probability of earthquake hazard before the Great East Japan Earthquake. These two terms control for firms' selection bias even before the earthquake. Lastly, MEA_{ir}^{2010} takes the value of 1 if firm i had a supplier in the top r-th metropolitan area in 2010 (and 0 otherwise). We include dummies for the top 10 metropolitan areas (e.g., Tokyo, Osaka, Nagoya), each of which are controlled for in order to capture the nature of large Japanese cities with higher likelihoods of larger earthquakes.

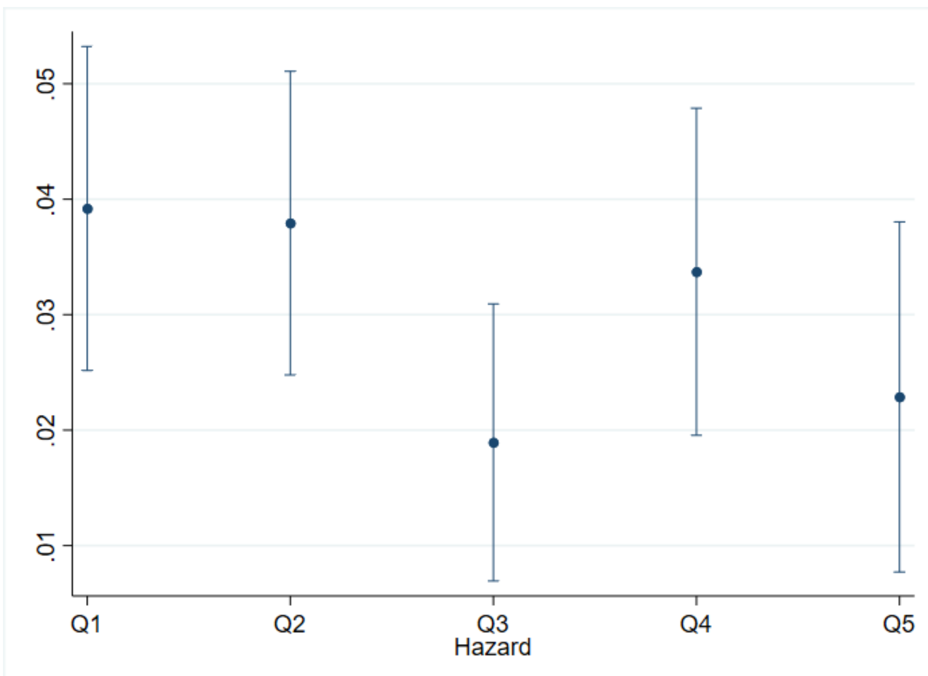
Figure 1.11 plots the coefficient for 2011 of equation (8) with the log numbers of new suppliers within quintile bands as outcomes.[22] The x-axis "Q1" refers to the band with hazard level lower than or equal to the 20th percentile, "Q2" the band with hazard level lower than or equal to the 40th percentile, "Q3" the band with hazard level lower than or equal to the 60th percentile, "Q4" the band with hazard level lower than or equal to the 80th percentile, and "Q5" the band with hazard level above the 80th percentile. The coefficients

[22] Figure 1.A20 shows the dynamics for each quintile band.

are all significant, which means that treated firms had new suppliers in every hazard quintile band. All of the estimates for quintiles 3 and 5 are smaller, i.e., 0.2, compared to those for quintiles 1 and 2, i.e., 0.4. However, the estimate for quintile 4 is around 3.5, and is not significantly different from the coefficients for quintiles 1 and 2.

Therefore, the seismological data reveal no clear pattern in supplier selection with respect to seismological risk. The estimated coefficients are neither increasing nor decreasing over quantile. It suggests that firms did not distinguish between "safe" and "more dangerous" locations when selecting new suppliers. Based on this finding, we could rule out the hypothesis that speaks to firms' information update on earthquake risks. In the next subsection, we discuss other potential factors that caused treated firm to significantly nearshore after the earthquake.

Figure 1.11. Hazard Forecasts: Log Number of New Suppliers Within Each Band



Note: This figure plots the coefficients for 2011 of difference-in-differences estimation with the log numbers of new suppliers within quintile bands as outcomes. Excluding the disaster area, we split the rest of Japan into quintile bands based on the hazard forecasts provided by National Research Institute for Earth Science and Disaster Prevention (NIED). The x-axis "Q1" refers to the band with hazard lower than or equal to 20th percentile, "Q2" refers to the band with hazard lower than or equal to 40th percentile, "Q3" the band with hazard lower than or equal to 60th percentile, "Q4" the band with hazard lower than or equal to 80th percentile, and "Q4" refers to the band with hazard above 80th percentile. The whiskers indicate the 95% confidence intervals based on the clustering in 2-digit industry code and prefecture code, and the dots indicate the point estimates of coefficients.

1.7.2 Discussion

The "nearshoring" by treated firms could be due to a combination of factors that caused them to put greater weight on geographical proximity. A possible scenario is that treated firms were forced to search in hurry for alternative suppliers in the wake of the disaster. They had not many choices and got matched with nearby suppliers. However, they then built up relational capital with those suppliers. This could explain why even after seven years from the disaster, treated firms did not return to distant suppliers that they used to source from.

It is hard to directly verify the accumulation of relational capital with nearby suppliers. Instead, we can examine if the duration of the relationships changed between pre- and post-disaster periods. As we discuss in the previous sections, the duration of relationships can be interpreted as the importance of the suppliers. To this end, we focus on the transaction relationships that started in 2008 and in 2011 and calculate the share of transaction relationships that lasted for the entire period within the same three-year window, i.e., 2008–2010 vs 2011–2013. We investigate the transaction relationships started in 2008 instead of 2007 since the sample period starts from 2007 and we cannot identify if a transaction that existed in 2007 actually started in 2007 or before that.

We find that the share of the transaction relationships that lasted for three years during the period is higher for those transaction relationships started in 2011 with suppliers located *outside* the disaster area. The share of the transaction relationships that lasted for three years during the period is 31.2% for those transaction relationships started in 2011 with suppliers located *outside* the disaster area, and 15.8% for those relationships started in 2008 with suppliers *inside* the disaster area. For control firms, the average duration of the transaction relationships did not change much. This is suggestive rather than conclusive evidence, but it supports the hypothesis that treated firms built up relational capital with alternative suppliers that they started trading with after the earthquake. The case is consistent with our findings that only treated firm significantly *nearshored*, whereas similar control firms did not.

Another possible scenario is that since the Great East Japan Earthquake, treated firms prioritized benefits of monitoring and acquiring information of suppliers' activities. As briefly discussed in the introduction, there is an example of Toyota Motor Corporation that compiled a comprehensive database of suppliers after 2011. The database covers not only direct suppliers but also indirect ones (e.g., Tier 1, 2 and 3 suppliers). The purpose is to build up a disaster-resilient supply chain and to highlight potential risks against sourcing inputs. This example shows that after the Great East Japan Earthquake, firms recognized the importance of acquiring information on suppliers. Because it would be much easier for firms to collect detailed information about supplier's production activities and their potential risks from nearby suppliers rather than distant ones, this could be another force behind nearshoring.

1.8 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 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' total number of suppliers remained broadly unchanged, compared to the control group firms; treated firms increased the number 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 14% 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. The seismological data reveal no clear pattern in supplier selection with respect to seismological risk. The results suggest that a combination of factors caused treated firms to place greater weight on proximity after a major supplier shock. We find suggestive evidence that firms built up relational capital with nearby suppliers after the Great East Japan Earthquake.

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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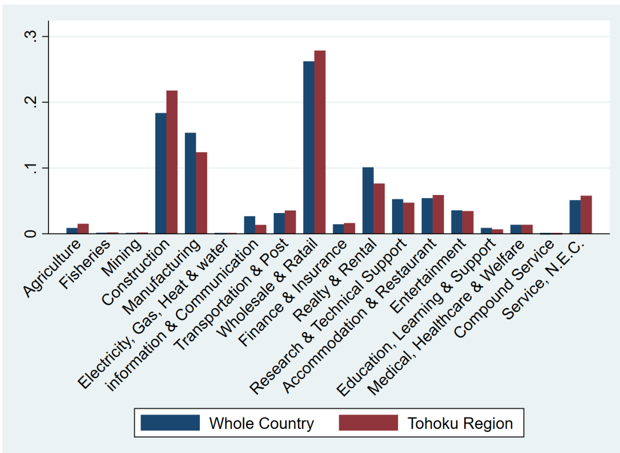
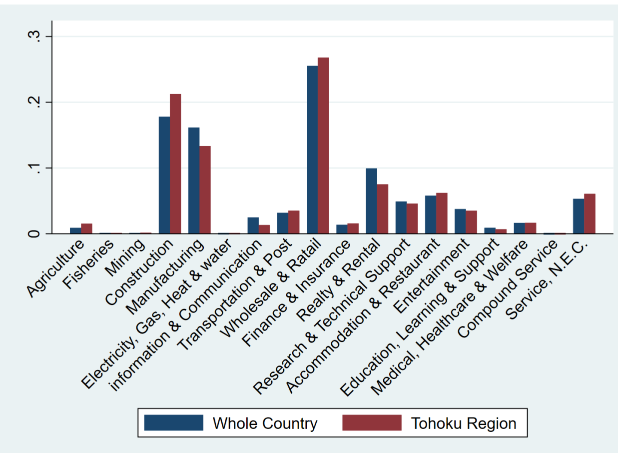
Appendix A Tables and Figures

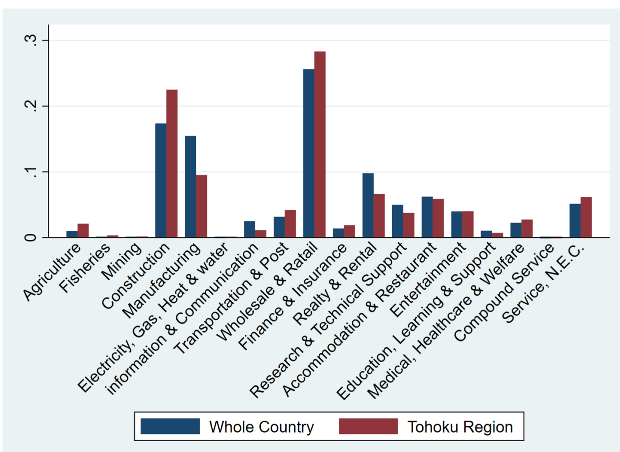
Figure 1.A1. Share of industries: Entire Country and Disaster-hit Area



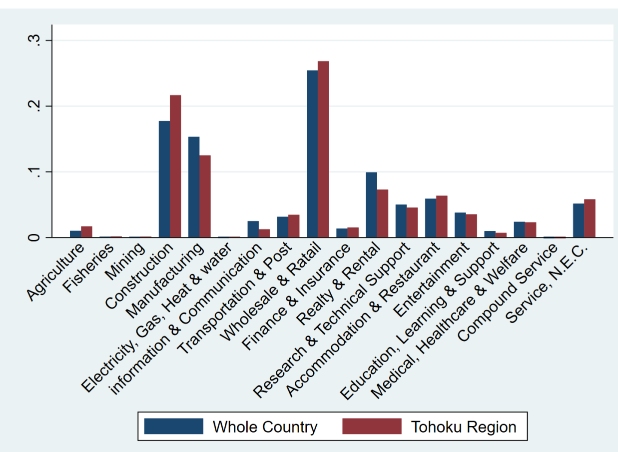
(a) 2009



(b) 2012



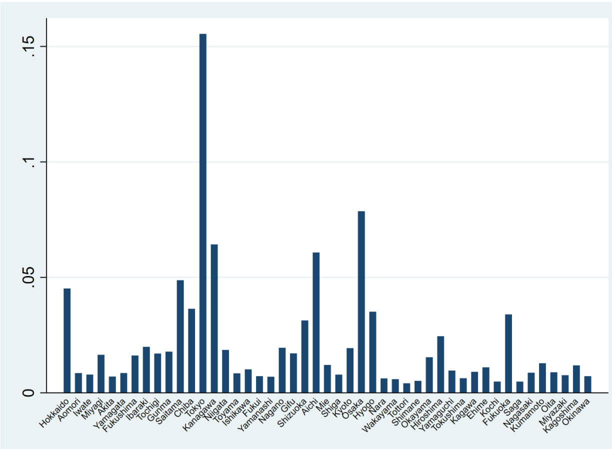
(c) 2014



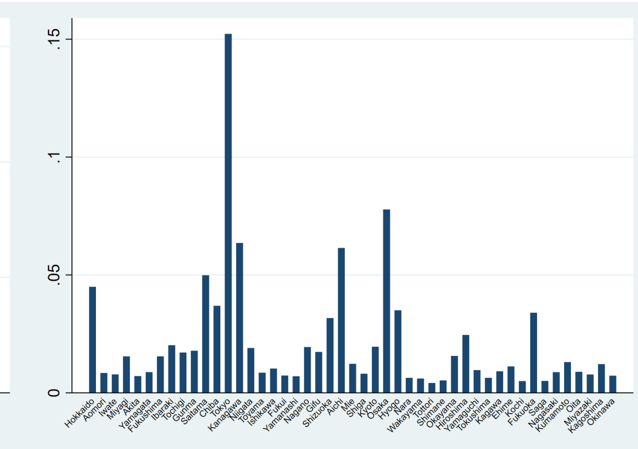
(d) 2016

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).

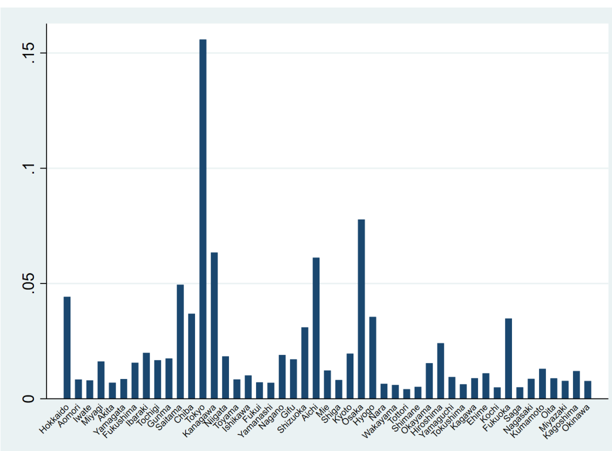
Figure 1.A2. Share of Firms by Prefecture



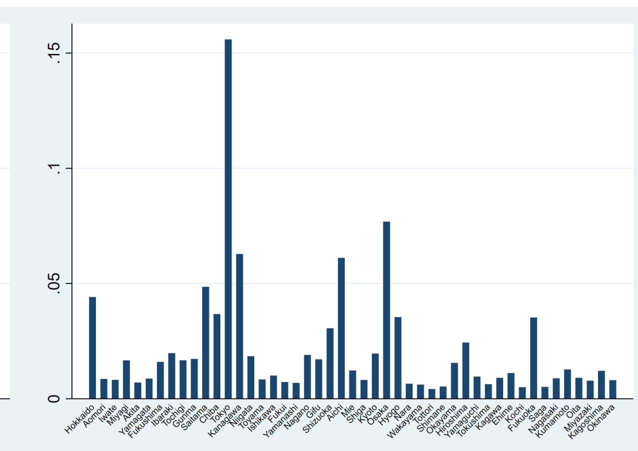
(a) 2009



(b) 2012



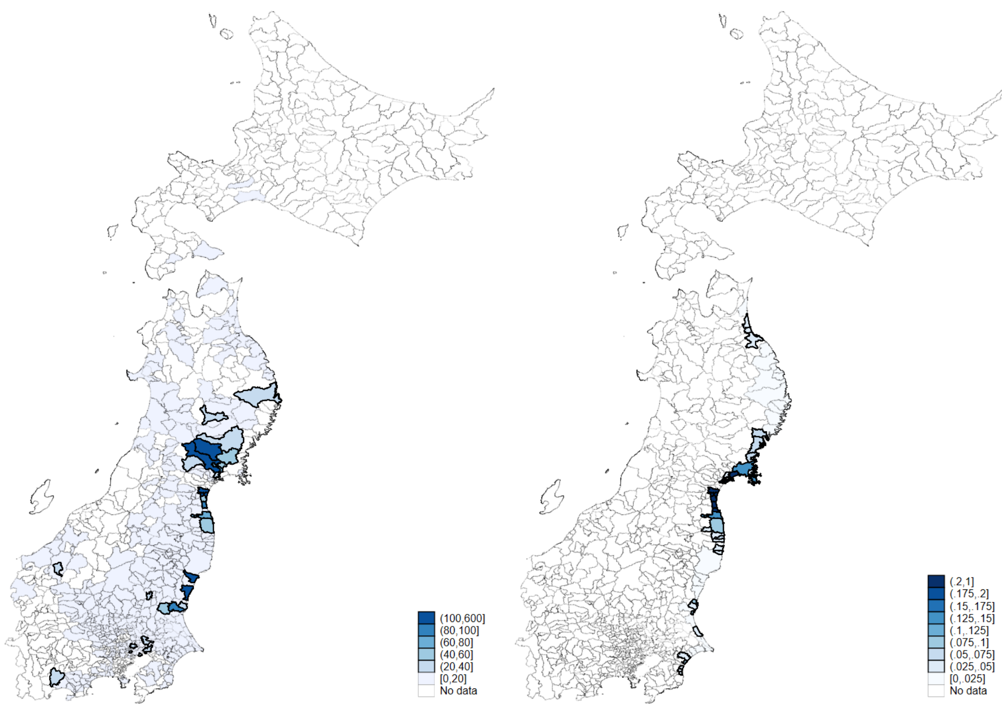
(c) 2014



(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).

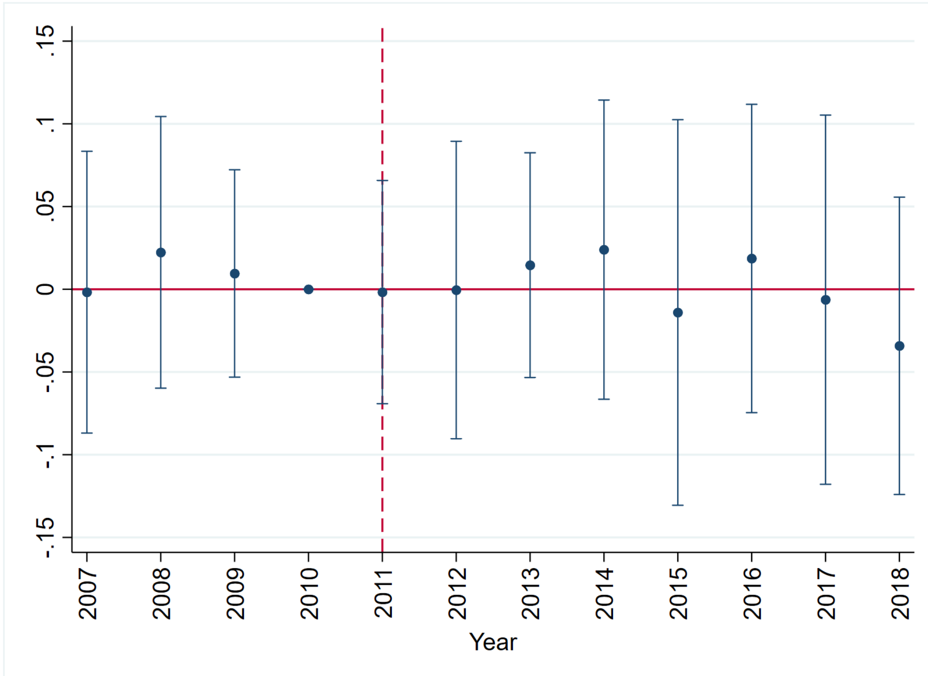
Figure 1.A3. The Geographical Distribution of Disaster Damages



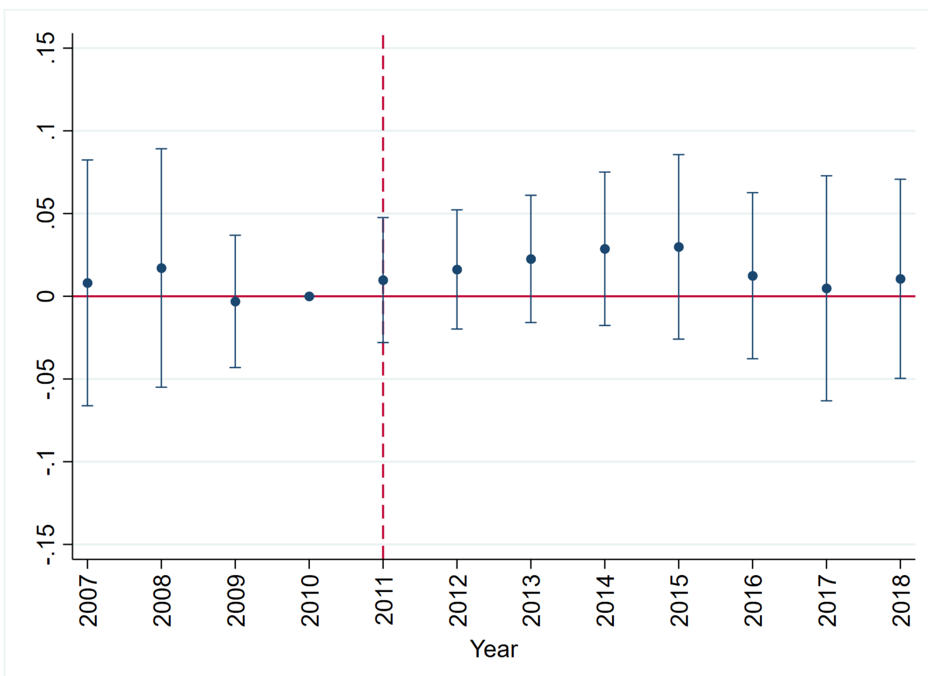
(a) Serious and Minor Injuries (b) Share of Flooded Area

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.

Figure 1.A4. Firm Sales and Employees: Exclude Firms with Degree 2–4



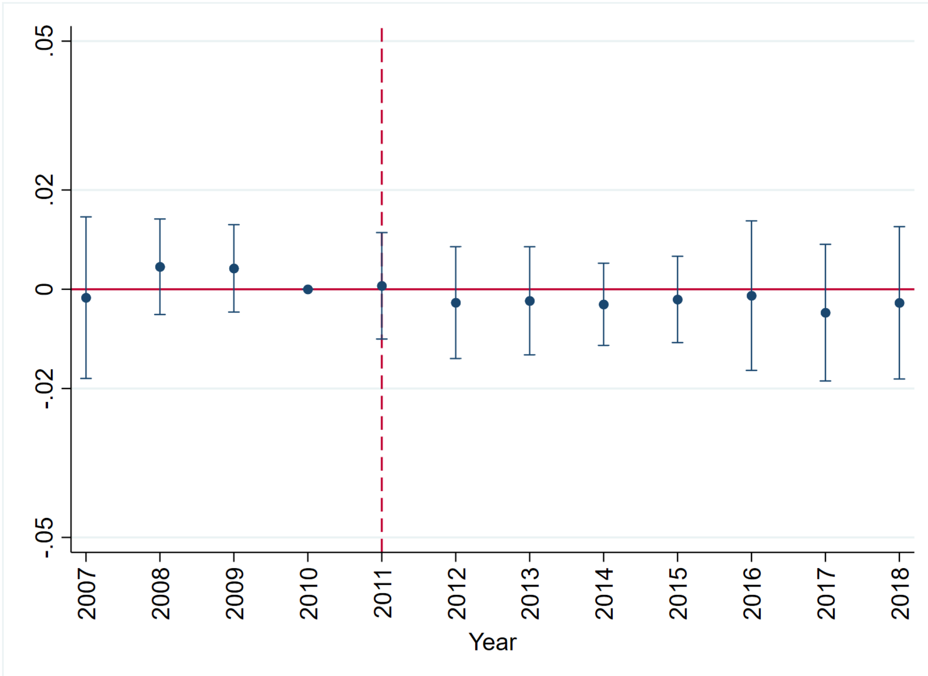
(a) Sales



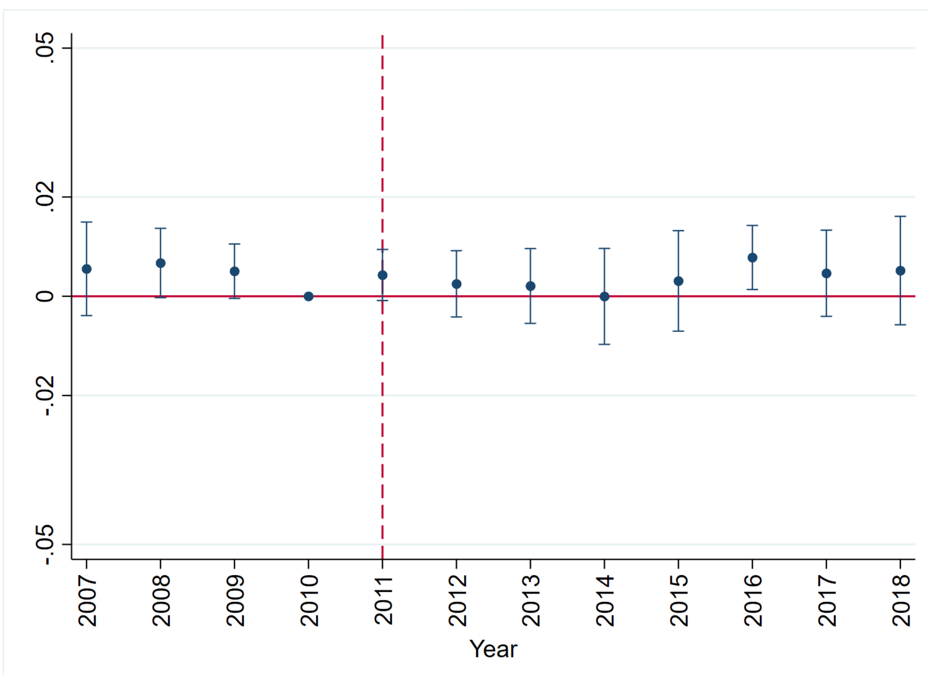
(b) Employment

Note: This figure plots the coefficients of a difference-in-differences estimation. Two panels correspond to (a) log firm sales, and (b) log number of employees. As a robustness check, we exclude firms with degree 2–4 from the control group. Here, degree is defined as the steps that it takes each firm along the production network to a supplier located inside the disaster area. 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 1.A5. Firm Sales: Replaces Sales after Exit with 0



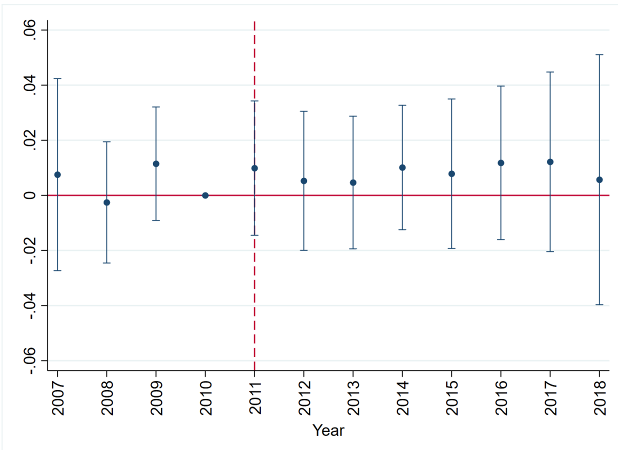
(a) Sales



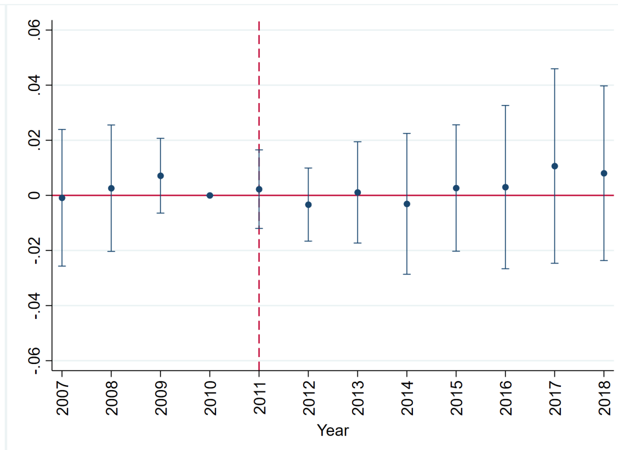
(b) Employment

Note: This figure plots the coefficients of a difference-in-differences estimation. Two panels correspond to (a) log firm sales, and (b) log number of employees. As a robustness check, we replace firm sales after exit with 0. 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.

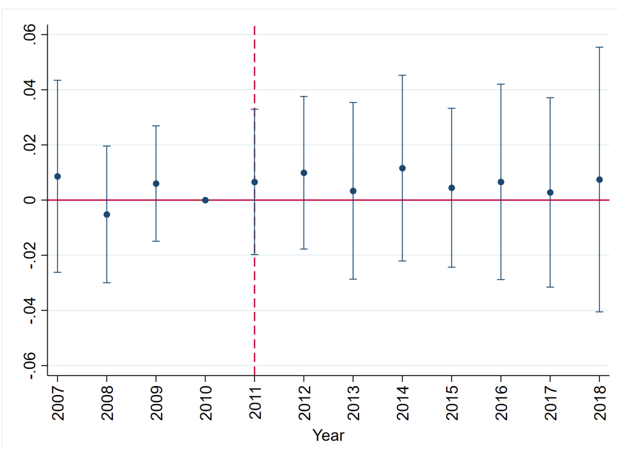
Figure 1.A6. The Impacts on Firm Performance: Manufacturing Sector



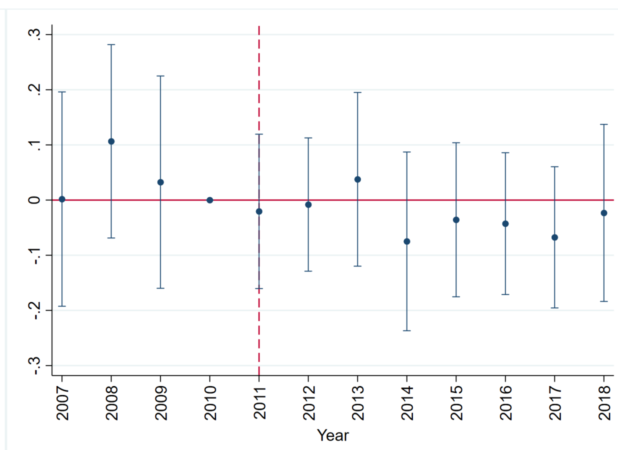
(a) Log Sales



(b) Log Employment



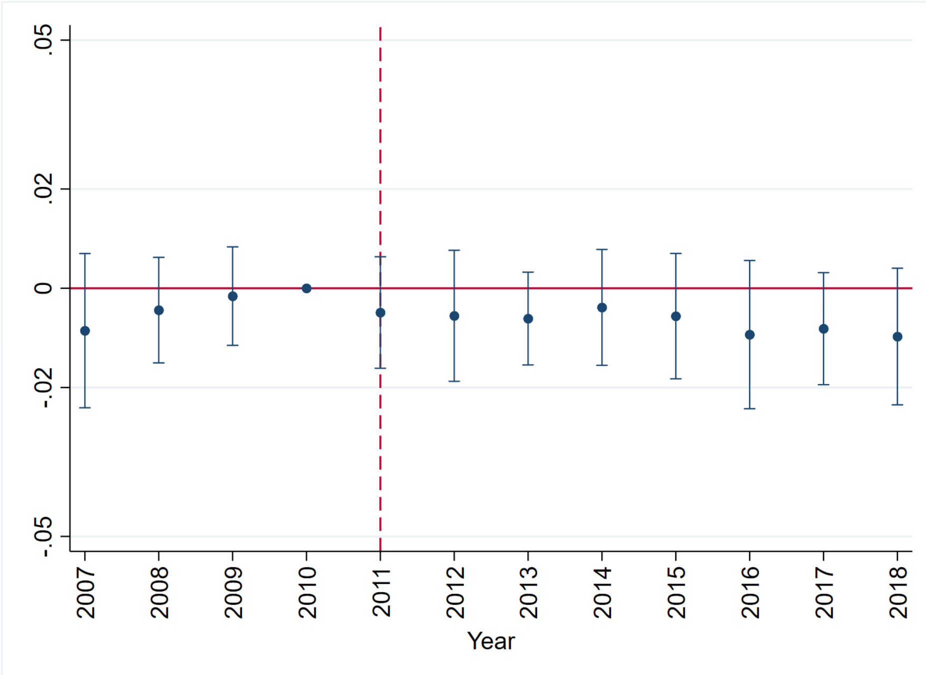
(c) Labor Productivity



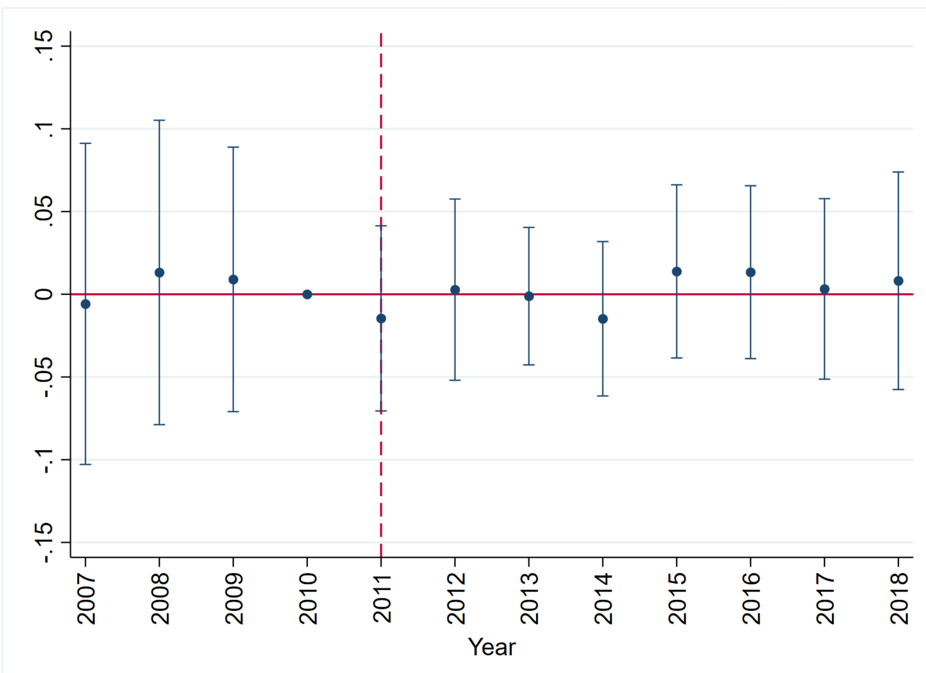
(d) ACF Productivity

Note: This figure plots the coefficients of difference-in-differences estimation with only firms in manufacturing sector. Four panels correspond to (a) log sales, (b) log number of employees, (c) labor productivity measures as sales divided by the number of employees, and (d) productivity estimated with the method of Ackerberg, Caves, and Frazer (2015). The whiskers indicate the 95% confidence intervals based on the clustering in 2-digit industry code and prefecture code, and the dots indicate the point estimates. The red vertical dotted line represents the year when the earthquake occurred.

Figure 1.A7. Productivity Measures Demeaned Within Industry



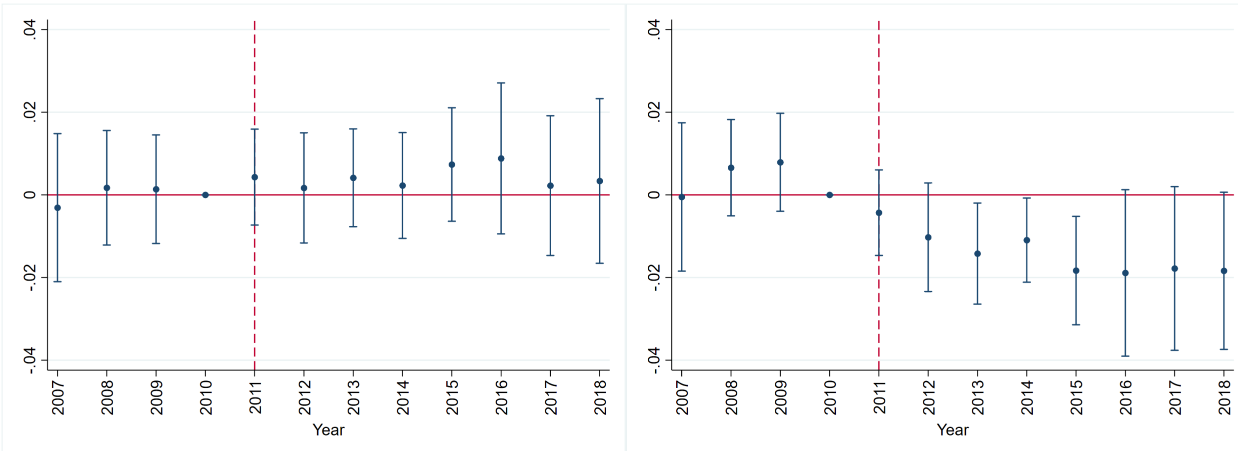
(a) Labor Productivity



(b) ACF Productivity

Note: This figure plots the coefficients of difference-in-differences estimation. Two panels correspond to (a) labor productivity measures as sales divided by the number of employees, and (b) productivity estimated with the method of Ackerberg, Caves, and Frazer (2015). Both productivity measures are demeaned within 3-digit industry. The whiskers indicate the 95% confidence intervals based on the clustering in 2-digit industry code and prefecture code, and the dots indicate the point estimates. The red vertical dotted line represents the year when the earthquake occurred.

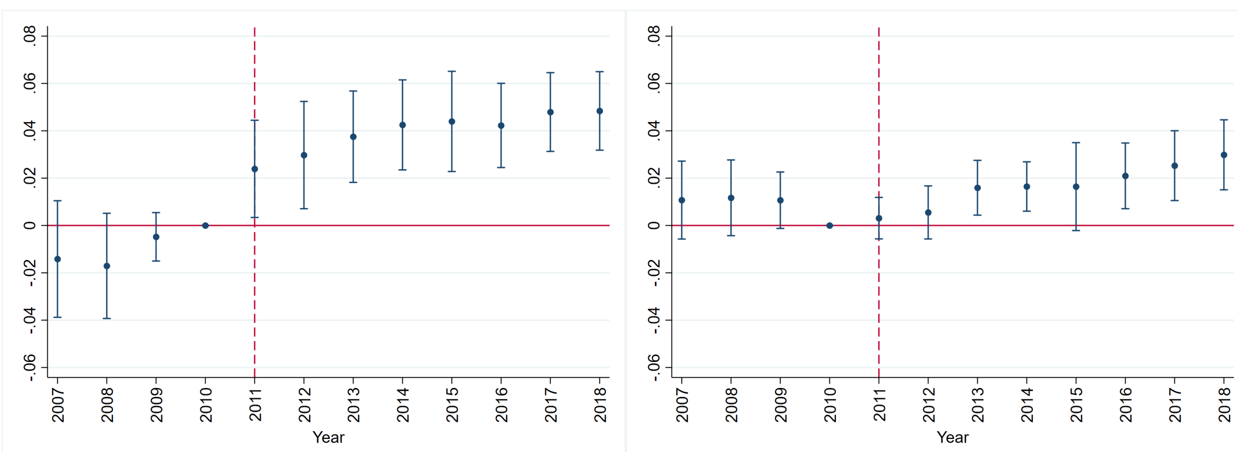
Figure 1.A8. Log Sales: Duration of Relationships



(a) Below Median (b) Above Median

Note: This figure plots the coefficients of difference-in-differences estimation. Two panels use log sales as the outcome. Panal (a) corresponds to buyer firms that had relationships with suppliers inside the disaster area for more than three years, and Panel (b) corresponds to the rest of firms. 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.

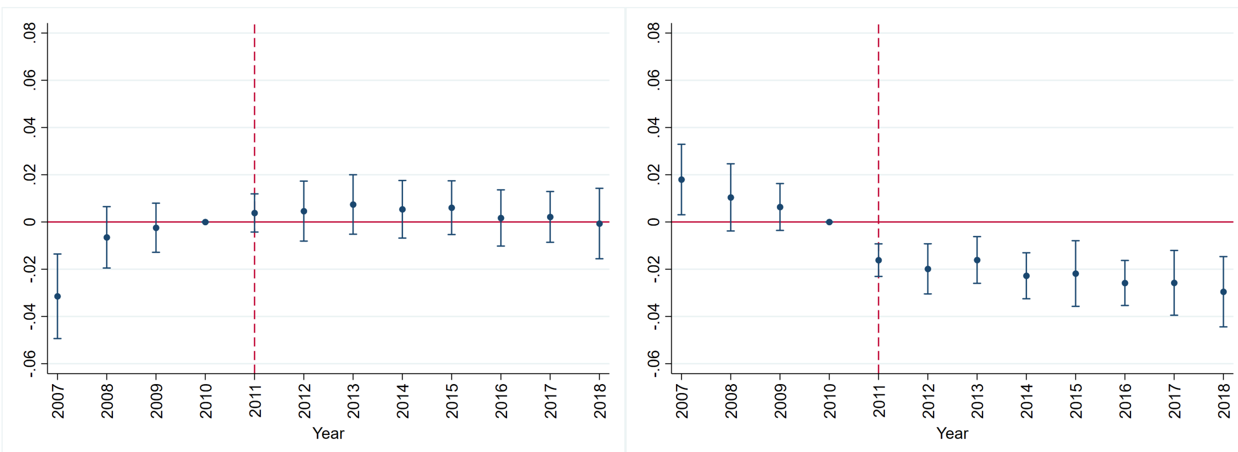
Figure 1.A9. Number of Suppliers Outside: Duration of Relationships



(a) Below Median (b) Above Median

Note: This figure plots the coefficients of difference-in-differences estimation. Two panels use log number of suppliers outside the disaster area as the outcome. Panal (a) corresponds to buyer firms that had relationships with suppliers inside the disaster area for more than three years, and Panel (b) corresponds to the rest of firms. 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.

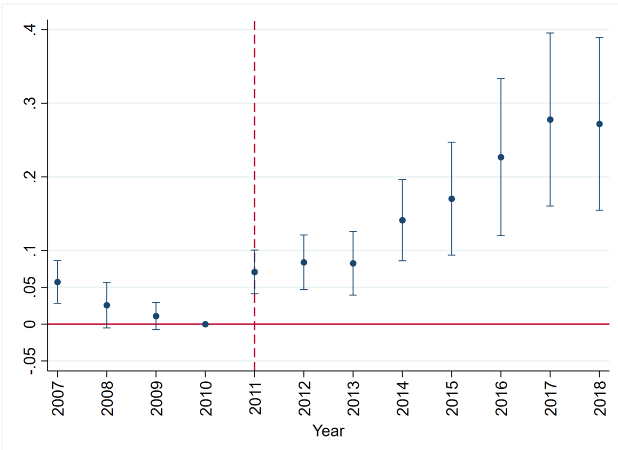
Figure 1.A10. Total Number of Suppliers: Duration of Relationships



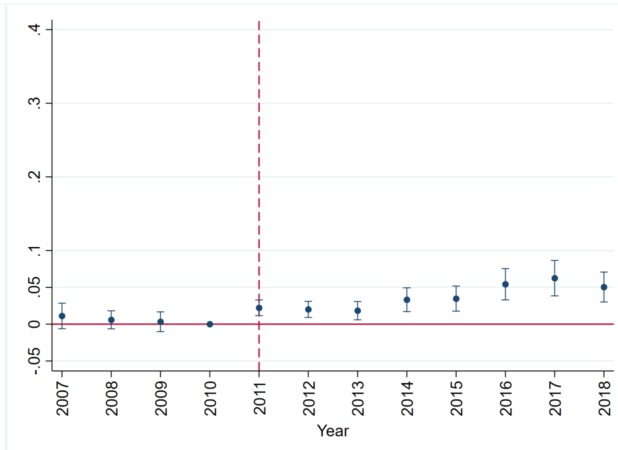
(a) Below Median (b) Above Median

Note: This figure plots the coefficients of difference-in-differences estimation. Two panels use log total number of suppliers as the outcome. Panal (a) corresponds to buyer firms that had relationships with suppliers inside the disaster area for more than three years, and Panel (b) corresponds to the rest of firms. 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.

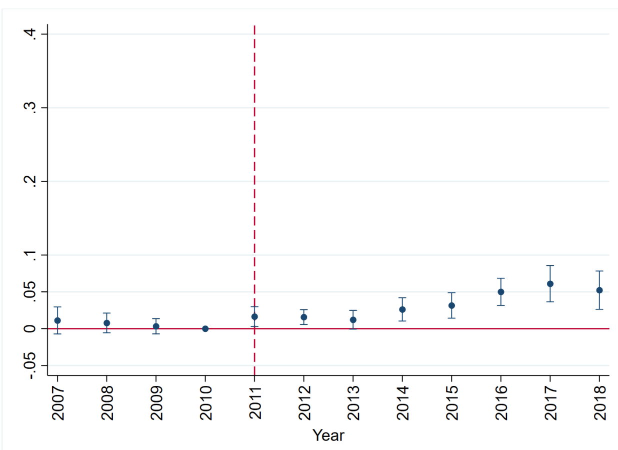
Figure 1.A11. Log Number of Suppliers Within Geographical Distance Bands



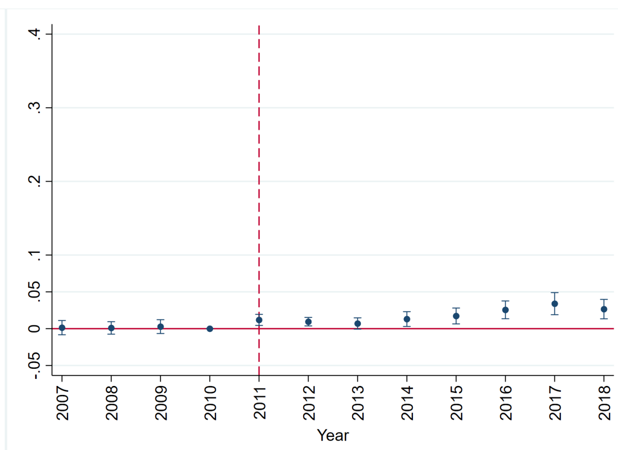
(a) 0–50 km



(b) 50–100 km



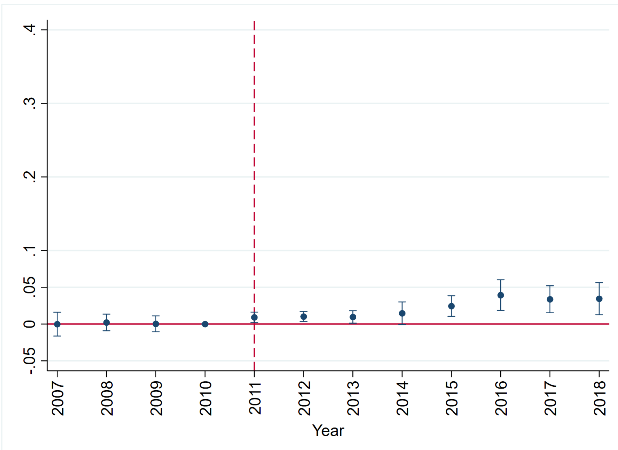
(c) 100–200 km



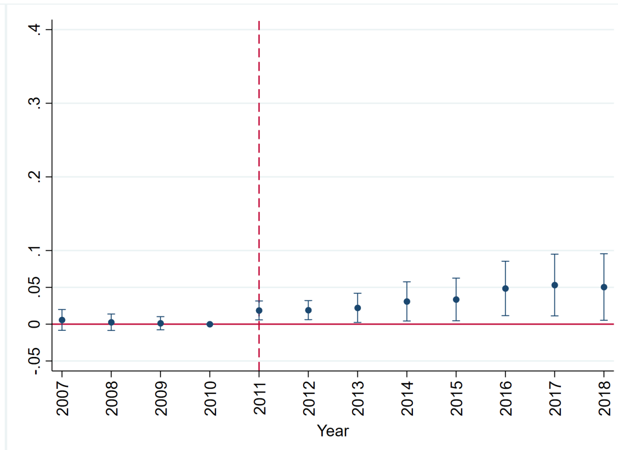
(d) 200–300 km

Note: This figure plots the coefficients of the dynamic 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 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 x-axis "50" refers to 0–50 km, "100" refers to 50–100 km, "200" refers to 100–200 km, "300" refers to 200–300 km, "400" refers to 300–400 km, "500" refers to 400–500 km, and "¿500" refers to beyond 500 km. The whiskers indicate the 95% confidence intervals based on the clustering in 2-digit industry code and prefecture code, and the dots indicate the point estimates of coefficients. The red vertical dotted line represents the year when the earthquake occurred.

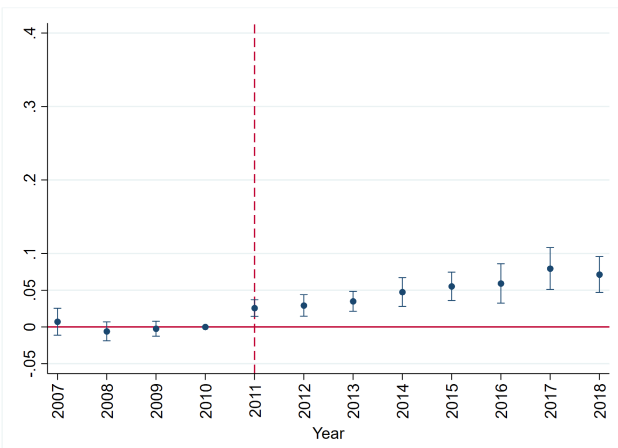
Figure 1.A12. Log Number of Suppliers Within Geographical Distance Bands, *Cont'd*



(a) 300–400 km



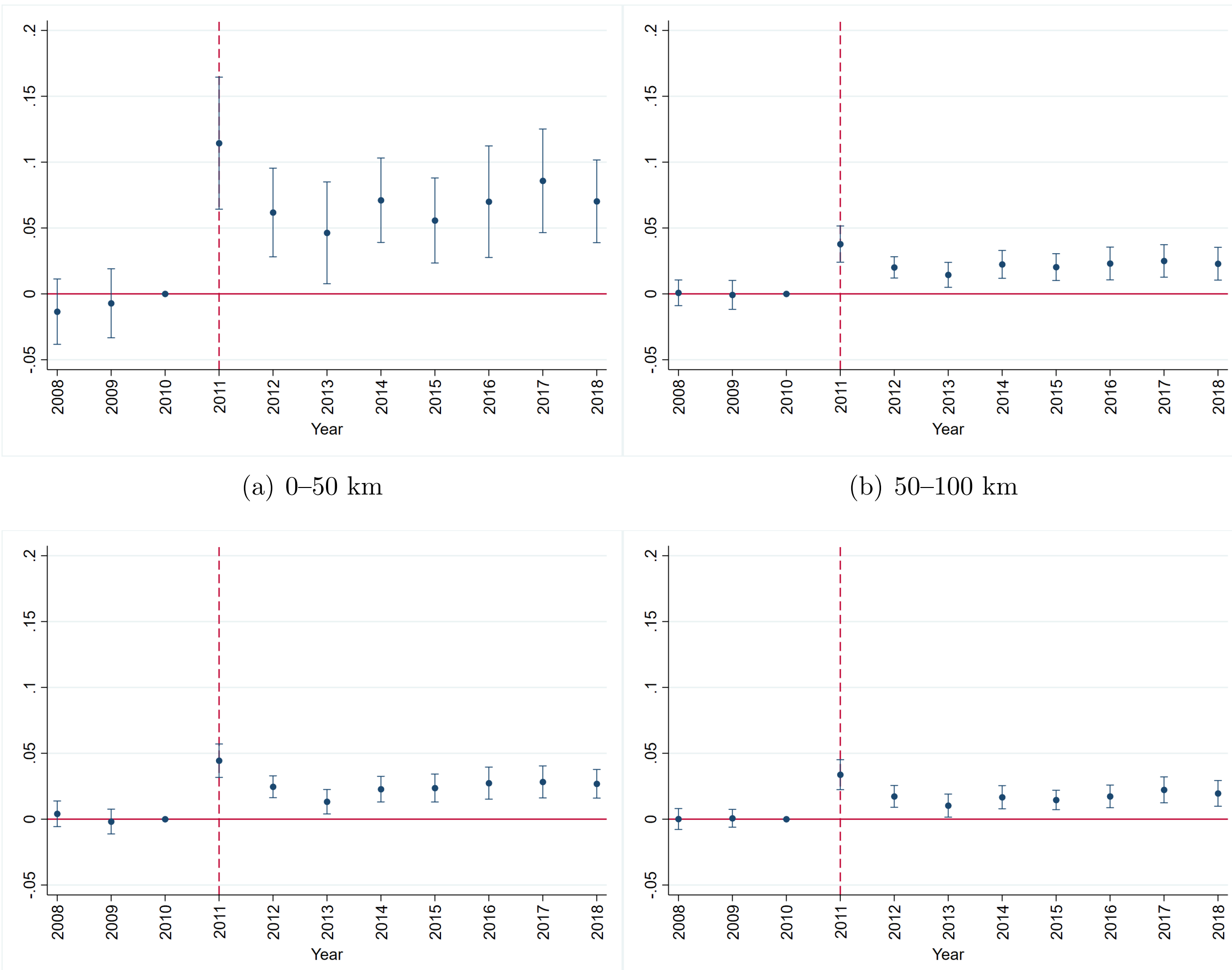
(b) 400–500 km



(c) Beyond 500 km

Note: This figure plots the coefficients of the dynamic 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 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 x-axis "50" refers to 0–50 km, "100" refers to 50–100 km, "200" refers to 100–200 km, "300" refers to 200–300 km, "400" refers to 300–400 km, "500" refers to 400–500 km, and "¿500" refers to beyond 500 km. The whiskers indicate the 95% confidence intervals based on the clustering in 2-digit industry code and prefecture code, and the dots indicate the point estimates of coefficients. The red vertical dotted line represents the year when the earthquake occurred.

Figure 1.A13. Log Number of New Suppliers Within Geographical Distance Bands



(a) 0–50 km

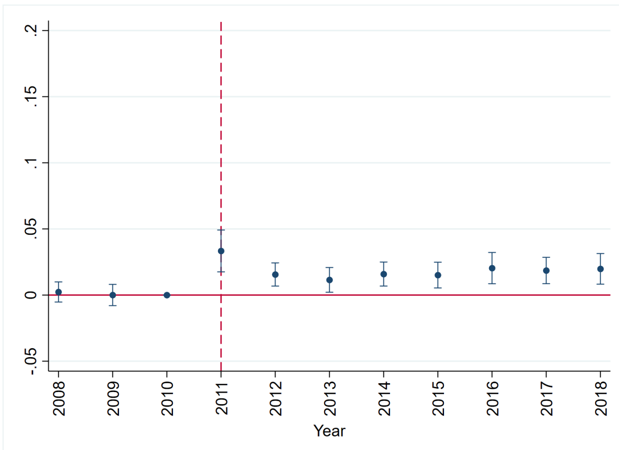
(b) 50–100 km

(c) 100–200 km

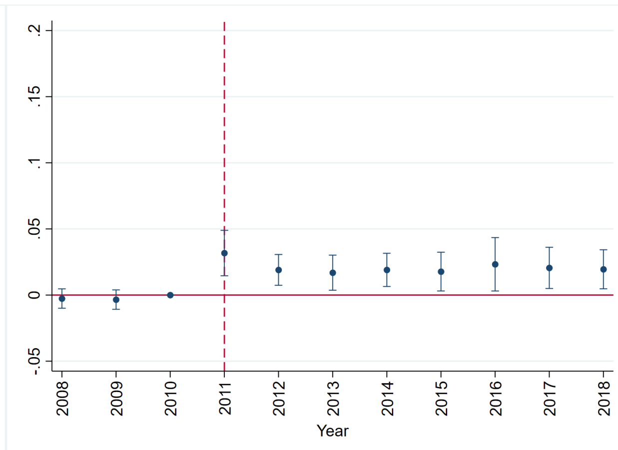
(d) 200–300 km

Note: This figure plots the coefficients of the dynamic 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 the 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 x-axis "50" refers to 0–50 km, "100" refers to 50–100 km, "200" refers to 100–200 km, "300" refers to 200–300 km, "400" refers to 300–400 km, "500" refers to 400–500 km, and "¿500" refers to beyond 500 km. The whiskers indicate the 95% confidence intervals based on the clustering in 2-digit industry code and prefecture code, and the dots indicate the point estimates of coefficients. The red vertical dotted line represents the year when the earthquake occurred.

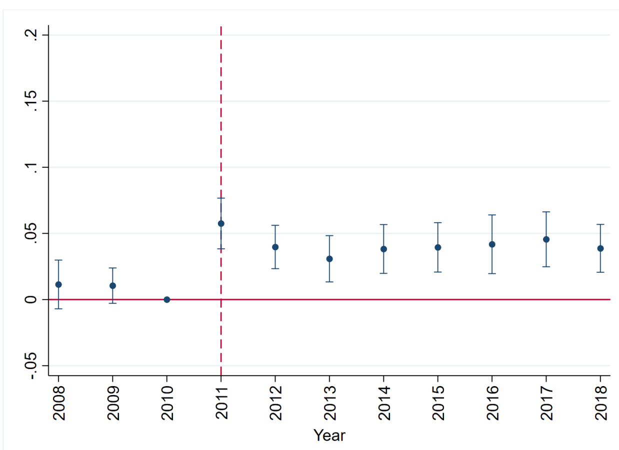
Figure 1.A14. Log Number of New Suppliers Within Geographical Distance Bands, *Cont'd*



(a) 300–400 km



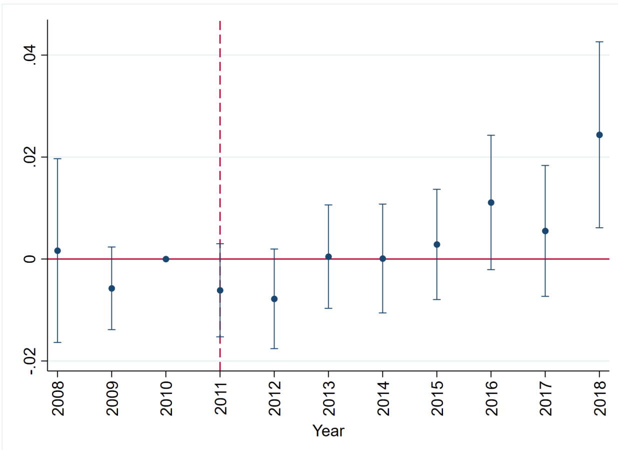
(b) 400–500 km



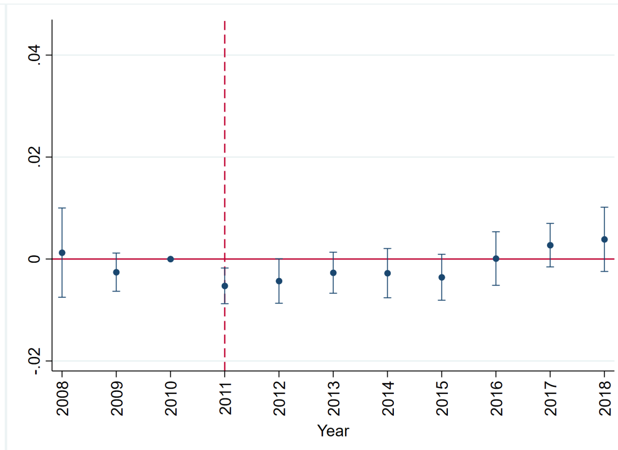
(c) Beyond 500 km

Note: This figure plots the coefficients of the dynamic difference-in-differences estimation with the log new numbers of suppliers within distance bands as outcomes. Excluding the disaster area, we split the rest of Japan into the 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 x-axis "50" refers to 0–50 km, "100" refers to 50–100 km, "200" refers to 100–200 km, "300" refers to 200–300 km, "400" refers to 300–400 km, "500" refers to 400–500 km, and "¿500" refers to beyond 500 km. The whiskers indicate the 95% confidence intervals based on the clustering in 2-digit industry code and prefecture code, and the dots indicate the point estimates of coefficients. The red vertical dotted line represents the year when the earthquake occurred.

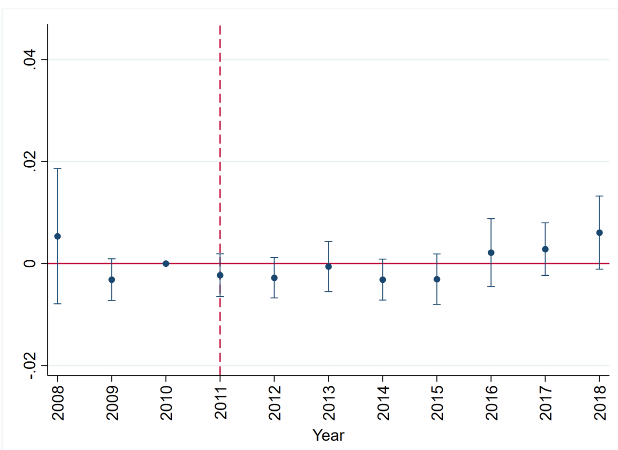
Figure 1.A15. Log Number of Dropped Suppliers Within Geographical Distance Bands



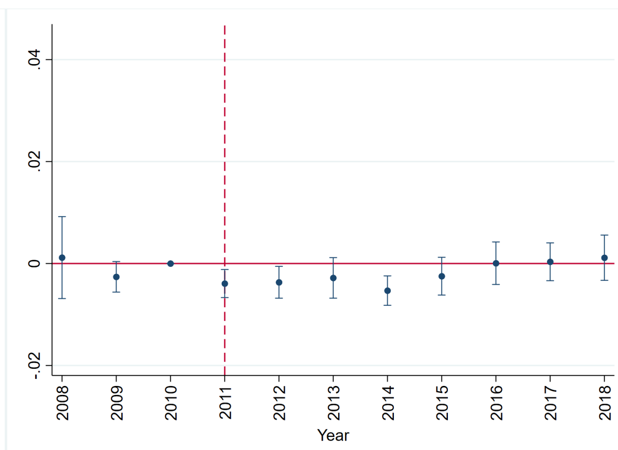
(a) 0–50 km



(b) 50–100 km



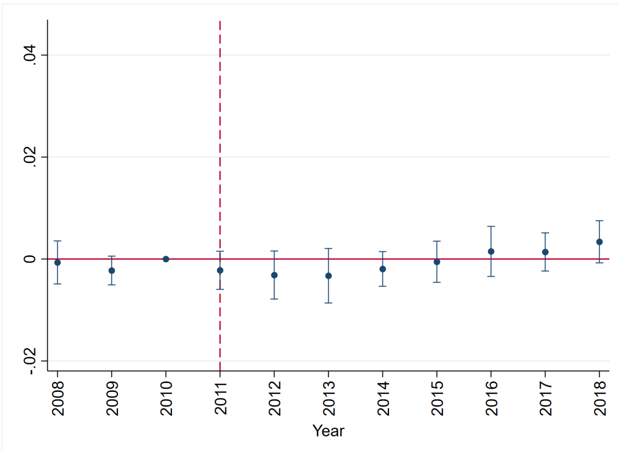
(c) 100–200 km



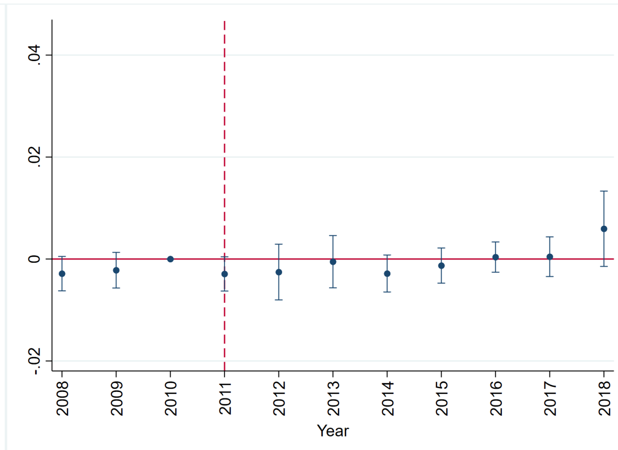
(d) 200–300 km

Note: This figure plots the coefficients of the dynamic difference-in-differences estimation with the log numbers of dropped suppliers within distance bands as outcomes. Excluding the disaster area, we split the rest of Japan into the 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 x-axis "50" refers to 0–50 km, "100" refers to 50–100 km, "200" refers to 100–200 km, "300" refers to 200–300 km, "400" refers to 300–400 km, "500" refers to 400–500 km, and "¿500" refers to beyond 500 km. The whiskers indicate the 95% confidence intervals based on the clustering in 2-digit industry code and prefecture code, and the dots indicate the point estimates of coefficients. The red vertical dotted line represents the year when the earthquake occurred.

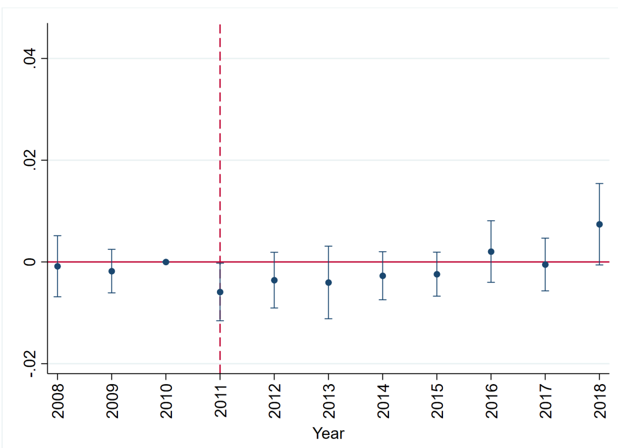
Figure 1.A16. Log Number of Dropped Suppliers Within Geographical Distance Bands, *Cont'd*



(a) 300–400 km



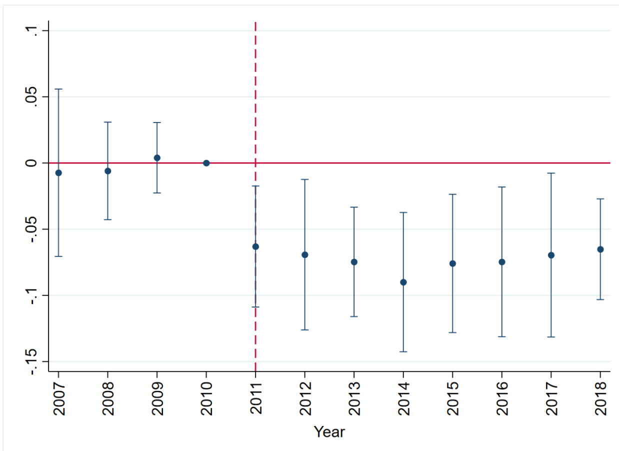
(b) 400–500 km



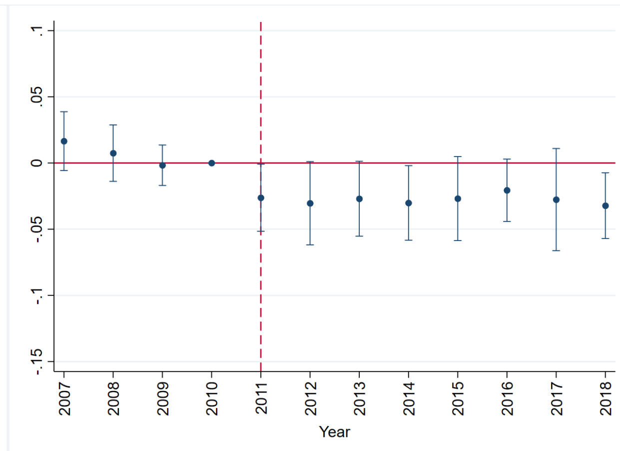
(c) Beyond 500 km

Note: This figure plots the coefficients of the dynamic difference-in-differences estimation with the log numbers of dropped suppliers within distance bands as outcomes. Excluding the disaster area, we split the rest of Japan into the 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 x-axis "50" refers to 0–50 km, "100" refers to 50–100 km, "200" refers to 100–200 km, "300" refers to 200–300 km, "400" refers to 300–400 km, "500" refers to 400–500 km, and "¿500" refers to beyond 500 km. The whiskers indicate the 95% confidence intervals based on the clustering in 2-digit industry code and prefecture code, and the dots indicate the point estimates of coefficients. The red vertical dotted line represents the year when the earthquake occurred.

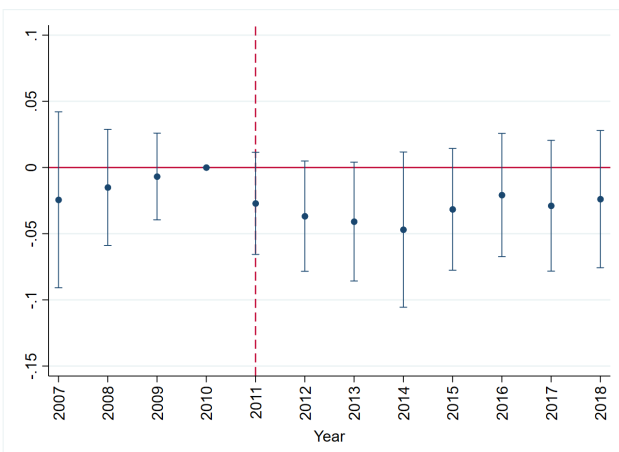
Figure 1.A17. Distance to Suppliers



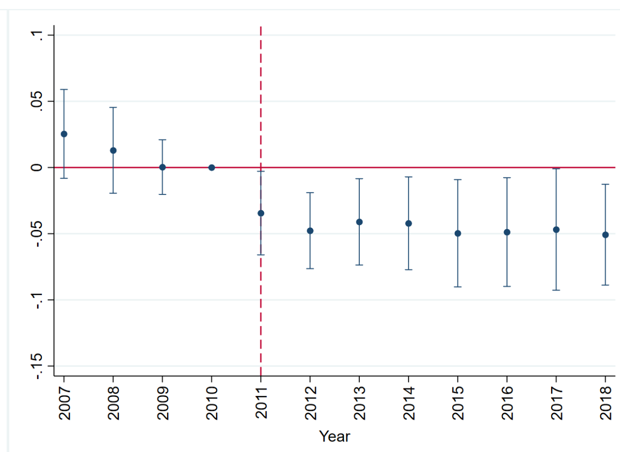
(a) Median Distance



(b) Maximum Distance



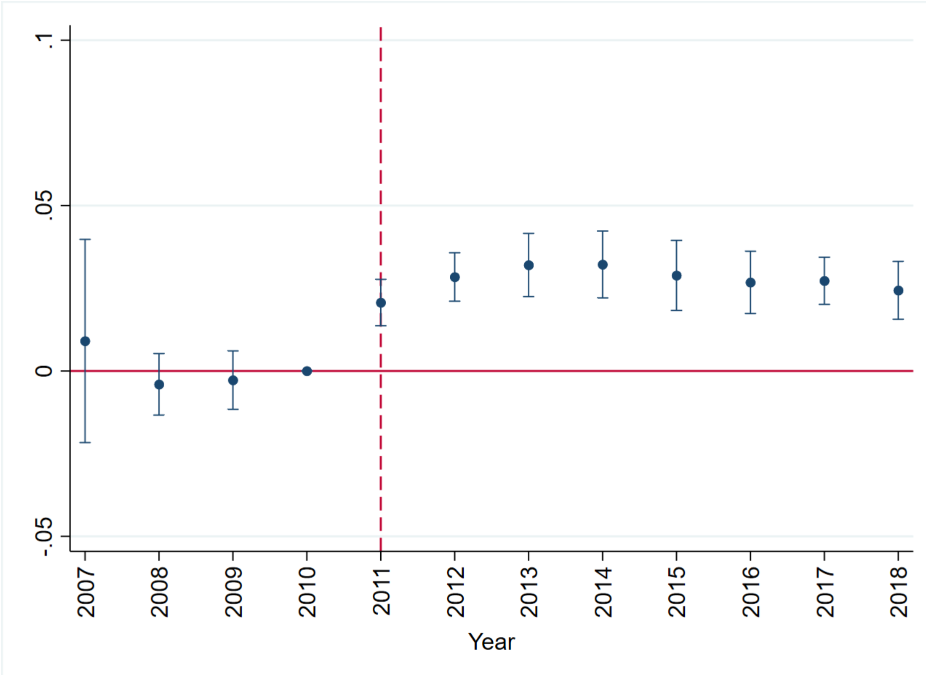
(c) Minimum Distance



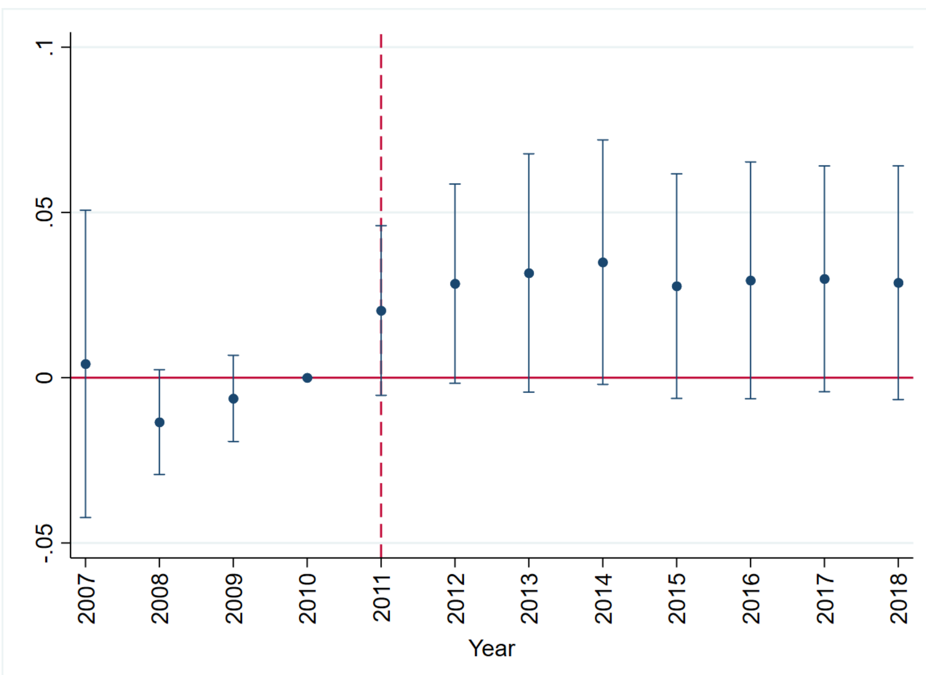
(d) SD of Distance

Note: This figure plots the coefficients of the event study design specification with the distance to suppliers as an outcome. We restrict the sample to those firms that lost at least one supplier inside the disaster area and added at least one supplier outside the disaster area between 2007–2010 and 2011–2014. Four panels correspond to median, maximum, minimum, and standard deviation of the distance. The whiskers indicate the 95% confidence intervals based on the clustering in 2-digit industry code and prefecture code, and the dots indicate the point estimates. The red vertical dotted line represents the year when the earthquake occurred.

Figure 1.A18. Share of Suppliers in the Same Regional Unit



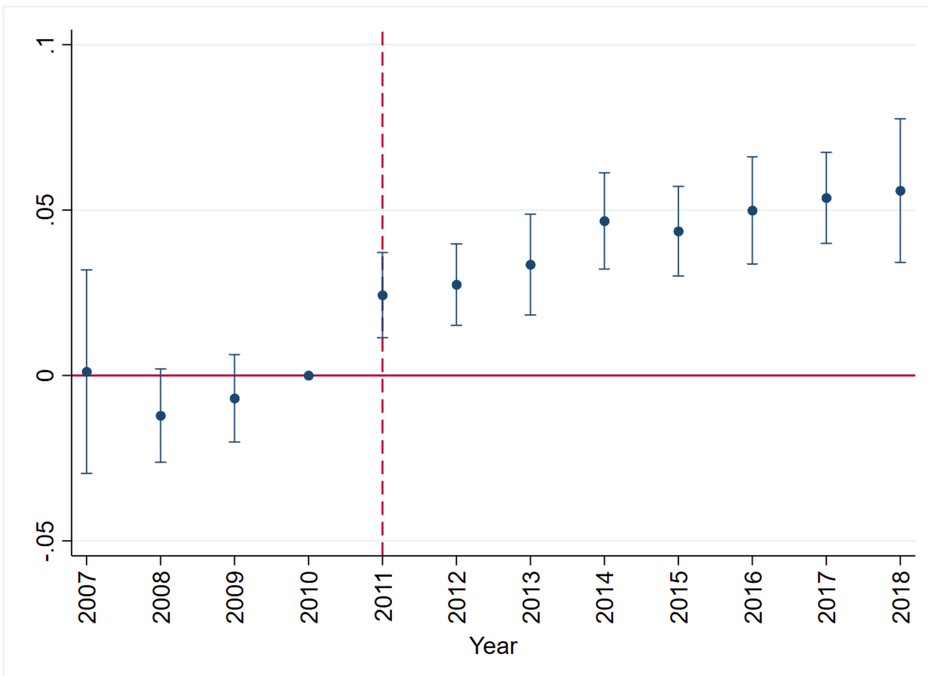
(a) Same Prefecture



(b) Same Region

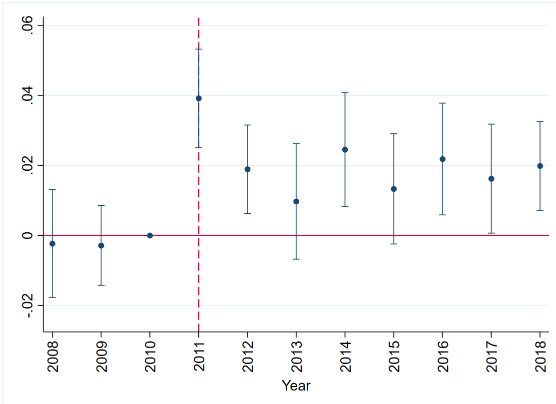
Note: This figure plots the coefficients of the event study design specification with the share of suppliers in the same regional unit as an outcome. We restrict the sample to those firms that lost at least one supplier inside the disaster area and added at least one supplier outside the disaster area between 2007–2010 and 2011–2014. Two panels correspond to the shares of suppliers in the same prefecture and that in the same region. The whiskers indicate the 95% confidence intervals based on the clustering in 2-digit industry code and prefecture code, and the dots indicate the point estimates. The red vertical dotted line represents the year when the earthquake occurred.

Figure 1.A19. Concentration Measure

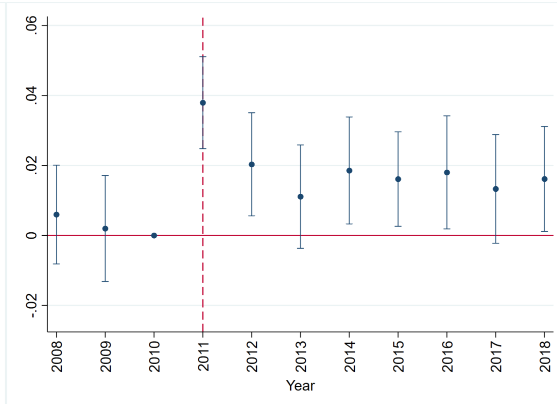


Note: This figure plots the coefficients of the event study design specification with the concentration measure as an outcome while restricting the sample to those firms that lost at least one supplier inside the disaster area and added at least one supplier outside the disaster area between 2007–2010 and 2011–2014. The whiskers indicate the 95% confidence intervals based on the clustering in 2-digit industry code and prefecture code, and the dots indicate the point estimates. The red vertical dotted line represents the year when the earthquake occurred.

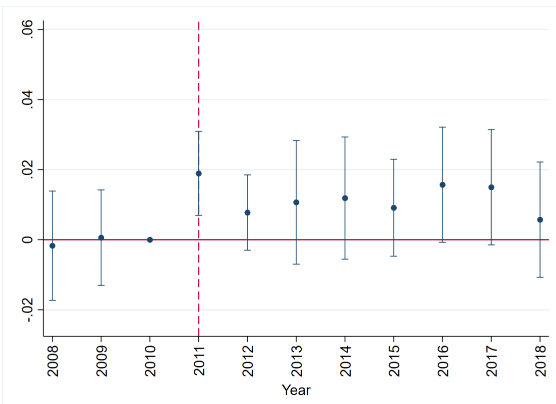
Figure 1.A20. Hazard Forecasts: Log Number of New Suppliers Within Each Band



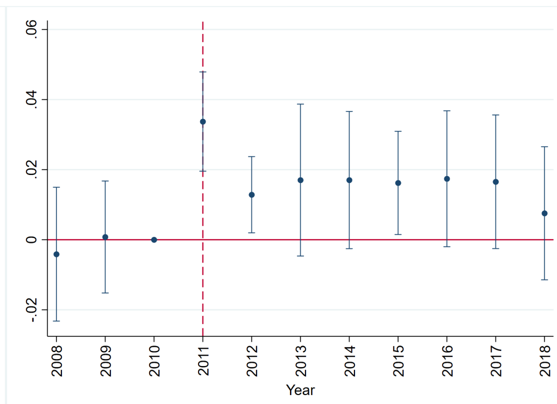
(a) Quintile 1



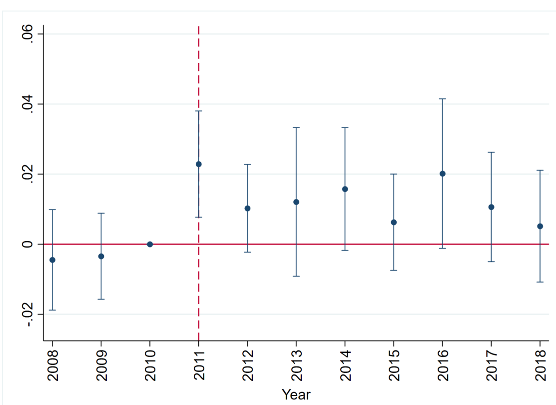
(b) Quintile 2



(c) Quintile 3



(d) Quintile 4



(e) Quintile 5

Note: This figure plots the coefficients of the dynamic difference-in-differences estimation with the log numbers of new suppliers within quintile bands as outcomes. Excluding the disaster area, we split the rest of Japan into quintile bands based on the hazard forecasts. Panels (a) refers to the band within hazard quintile 1, (b) the band within hazard quintile 2, (c) the band within hazard quintile 3, (d) the band within hazard quintile 4, and (e) refers to the band within hazard quintile 5. The whiskers indicate the 95% confidence intervals based on the clustering in 2-digit industry code and prefecture code, and the dots indicate the point estimates of coefficients.

Appendix B Updated Information on Firms

B.1 Differences in Data Construction: This Paper and Carvalho et al. (2021)

This subsection explains the difference in data construction approaches between our study and Carvalho et al. (2021), both of which use the Tokyo Shoko Research (TSR) data. TSR collects information in September of each year and updates the dataset annually. The TSR data for each year essentially contain the information on firms that have closed their accounts in the past 61 months (about 5 years). For instance, the data for 2010 basically includes the information on firms that closed their accounts between September 2005 and September 2010.

We combine the raw TSR data from 2007 to 2019 and use the most latest response for firm i in sample year from 2007–2018, as the observed values in our dataset. Additionally, we create the panel data for the sample of year t using firms whose fiscal years conclude in January through December of that year. Carvalho et al. (2021) on the other hand, employ the following sample of firms for their regression analysis. From the TSR data for year t, they take firms whose fiscal year ends between April of year $t-1$ and March of year t as the data for fiscal year $t-1$.

The incorporation of updated information distinguishes our dataset from that of Carvalho et al. (2021). While Carvalho et al. (2021) do not exploit the late responses but use the set of firms observed over a particular period for the TSR data in year t as the data for fiscal year $t-1$, our dataset utilizes all the updated information. If a firm i only responds in year t with its financial information for year t, that firm's information is recorded in both ours and Carvalho et al. (2021)'s approach. However, if firm i only responds in year $t+s$ ($s>0$) with its financial information for year t, it is excluded from the dataset under Carvalho et al. (2021)'s approach. In addition, for the case that a firm responded in both year t and year $t+s$, Carvalho et al. (2021)'s approach does not use the information for year $t+s$, even if a firm updates its information in year $t+s$. We have compared our data construction approach with that of Carvalho et al. (2021) to see to what extent data construction approach affect sample size; ours increased the number of observations by about 15% in raw data. This fact indicates that our data construction method covers a larger number of firms than that of Carvalho et al. (2021).

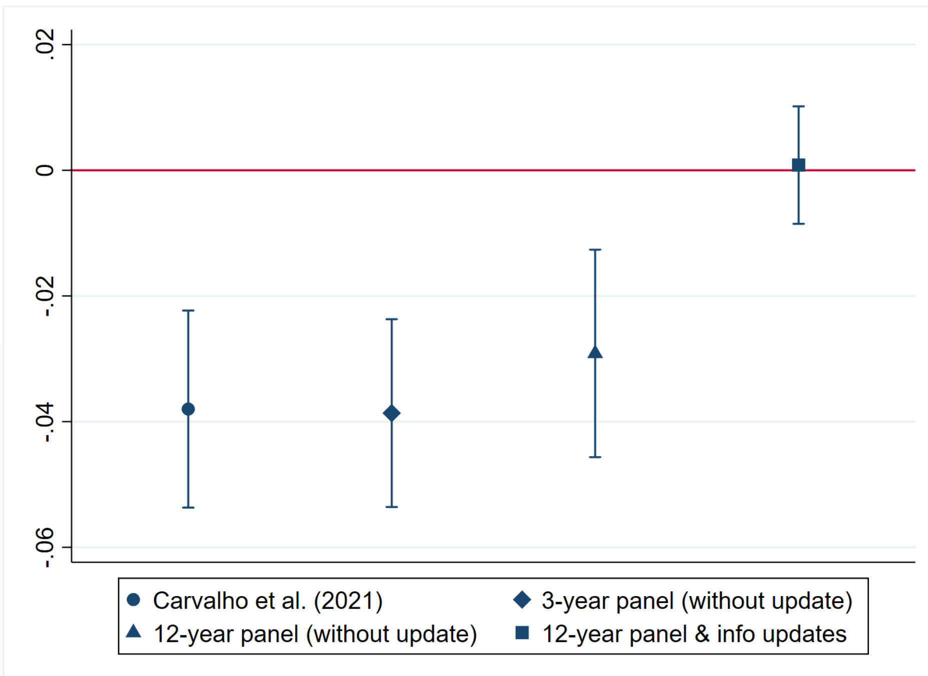
B.2 Comparing Estimates: This study and Carvalho et al. (2021)

In this subsection, we investigate the extent to which our data construction approach yields estimation results that differ from those of Carvalho et al (2021). They estimate the effect of the earthquake's propagation through the supply chain on the sales of firms located outside the disaster area. We use the same dataset and define the treatment group as they did.

To confirm our findings, we conduct three set of replication exercises. We concentrate on the immediate customers of disaster-area firms for make comparisons. Figure 1.B1 displays four sets of estimates for the year immediately following the earthquake: (1) those made in Carvalho et al. (2021) using the data for 2010–2012, (2) those made using the dataset produced in accordance with Carvalho et al. (2021)'s data construction approach (i.e., without using late responses) for 2010–2012, (3) those made using the dataset produced in accordance with Carvalho et al. (2021)'s data construction approach (i.e., without using late responses) for 2007–2018, and (4) those made using the study's data construction approach (i.e., with using late responses) using the data for 2007–2018. As we discuss in the previous subsection, from this approach, we increase the number of non-missing observations by almost 15%.

The results are as follows. First, by comparing the estimates of (1) and (2), it is shown that we successfully replicate the result provided by Carvalho et al. (2021). These two estimates are both negative, almost identical in size and statistically significant. Second, after extending the sample period to 2007–2018, we obtain similar the estimate, which is negative and statistically significant as shown in Figure 1.B1. However, the estimate in (4) becomes negligible in its size and statistically insignificant. Thus, the last exercise (4) includes a larger number of firms, and demonstrates that on average, there is no differential impact of the earthquake on treated firms.

Figure 1.B1. Comparing Four Different Estimates for 2011



Note: This figure displays four sets of estimates for the year immediately following the earthquake: (i) those made in Carvalho et al. (2021) using the dataset between 2010 and 2012, (ii) those made using the dataset between 2010 and 2012 produced in accordance with Carvalho et al. (2021)'s data construction approach (i.e., without using late responses), (iii) those made using the dataset between 2007 and 2018 produced in accordance with Carvalho et al. (2021)'s data construction approach (i.e., without using late responses), and (iv) those made using the study's data construction approach (i.e., with using late responses).

Appendix C 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. Table 1.C1 shows the mean values of each variable before and after matching separately in Unmatched (U) and Matched (M) rows. We can see a difference in the mean values of each variable between the treatment and control groups. The right-most column shows the results of the balancing t-test. After matching, we find that the sample has much smaller difference in covariates between treatment and control groups, suggesting that the matching works effectively.

The results are as follows. First, Figure 1.C1 presents the estimation results of firms' performance, which corresponds to Figure 1.2 in the baseline. Second, Figure 1.C2 presents the estimation results of firms' restructuring of supplier relationships, which corresponds to Figure 1.3. Third, Figure 1.C3 shows the PSM estimation results for log number of suppliers within distance bands, which corresponds to the baseline result shown in Figure 1.6. Similarly, Figure 1.C4 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 1.9.

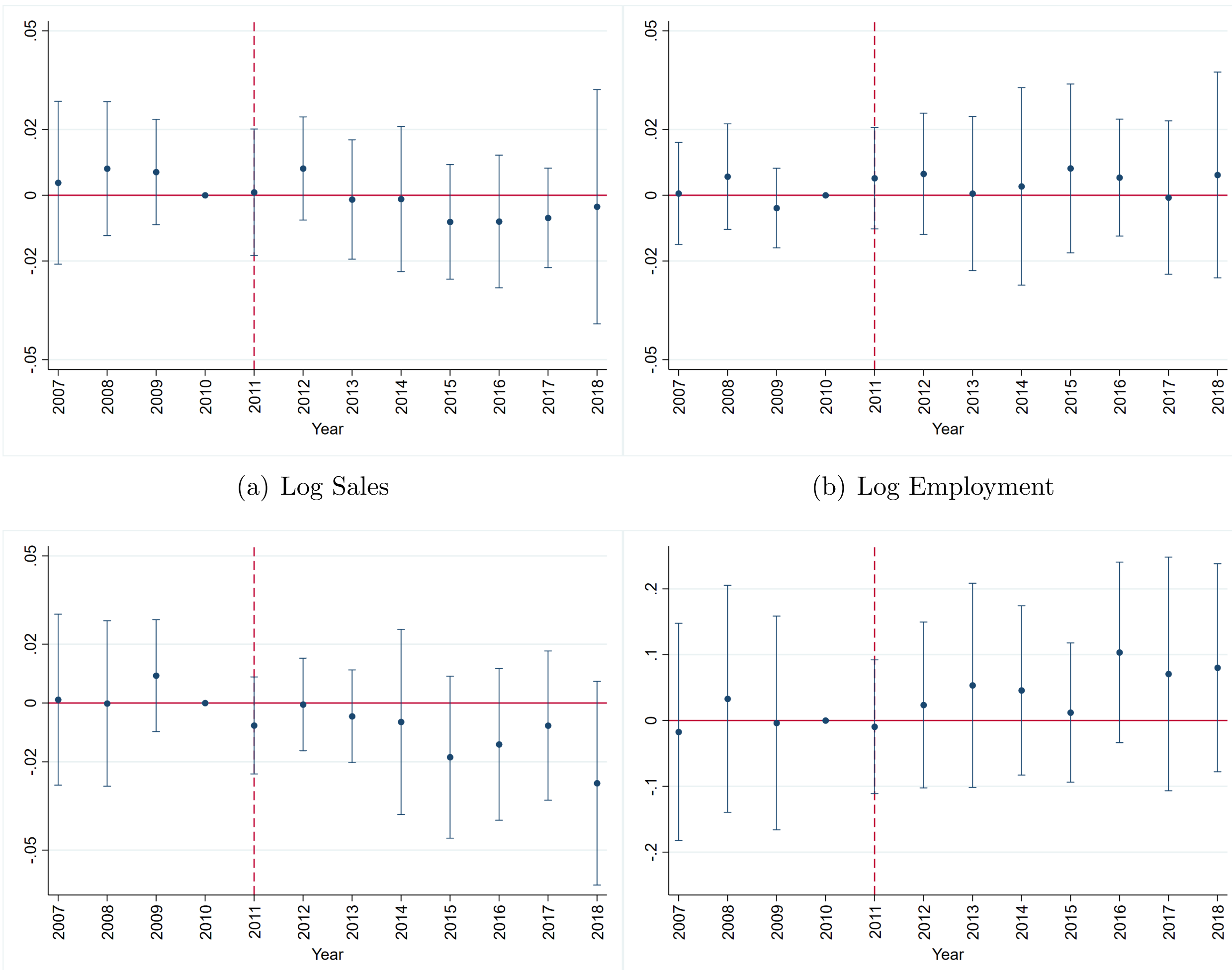
Fourth, the results of Figure 1.C5 correspond to the baseline result of Figure 1.A17. Similarly, Figure 1.C6 shows the results with the share of suppliers in the same regional unit as an outcome, corresponding to Figure 1.A18. Figure 1.C7 shows the results of the difference-in-difference estimation with the concentration measure as an outcome. The concentration measure increased sharply since the Great East Japan Earthquake, as shown in Figure 1.A19. All results shown here are similar to those obtained in the baseline estimation and confirm that our findings are robust.

Table 1.C1. Balancing Tests Before and After Propensity Score Matching

Variables	Match	Treated	Control	Bias	t-stat
Panel A: Benchmark					
Firm age	U	31.76	28.861	17.6	12.08***
Log # of workers	U	3.142	2.287	57.8	44.93***
Log total # of links	U	2.481	1.901	64.9	50.11***
Distance to the disaster area	U	260.79	484.28	-73.4	-42.25***
Panel B: Propensity Score Matching					
Firm age	M	31.706	32.11	-2.5	-1.13
Log # of workers	M	3.134	3.152	-1.2	-0.52
Log total # of links	M	2.474	2.491	-1.9	-0.79
Distance to the disaster area	M	261.36	259.74	0.5	0.31

Note: Panel A shows the statistics for benchmark sample. Panel B shows the statistics for sample after conducting propensity score matching. Log total number of links refers to the log total number of suppliers and customers. Columns of Treated and Control show the mean values of each variable. ***, **, and * denotes statistical significance at the 1%, 5%, and 10% levels, respectively. Lastly, t-stat denotes the results of balancing t-test for each matched and unmatched sample.

Figure 1.C1. The Impacts on Firm Performance



(a) Log Sales

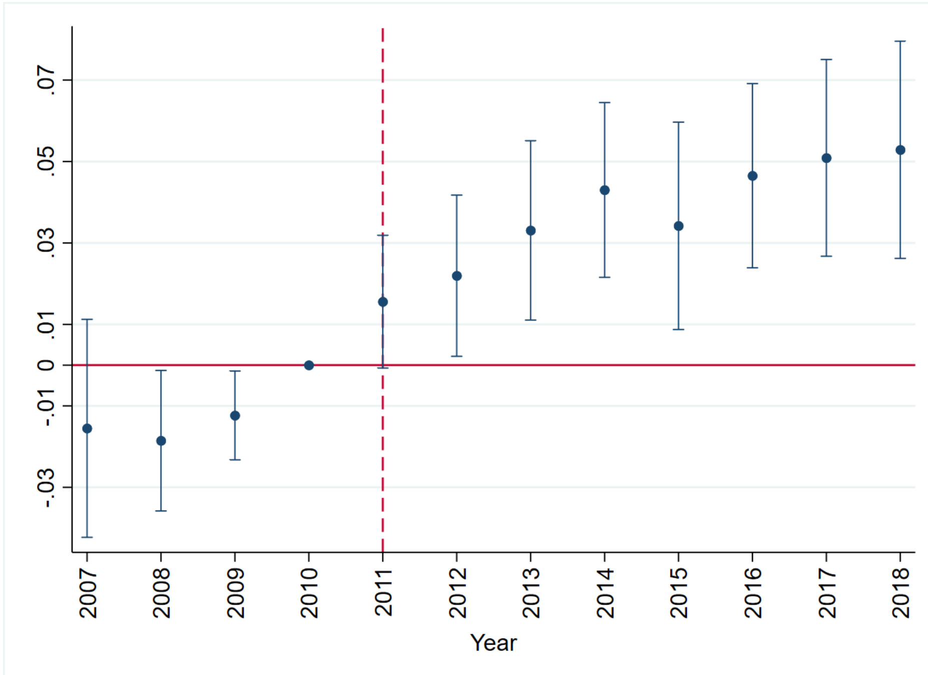
(b) Log Employment

(c) Labor Productivity

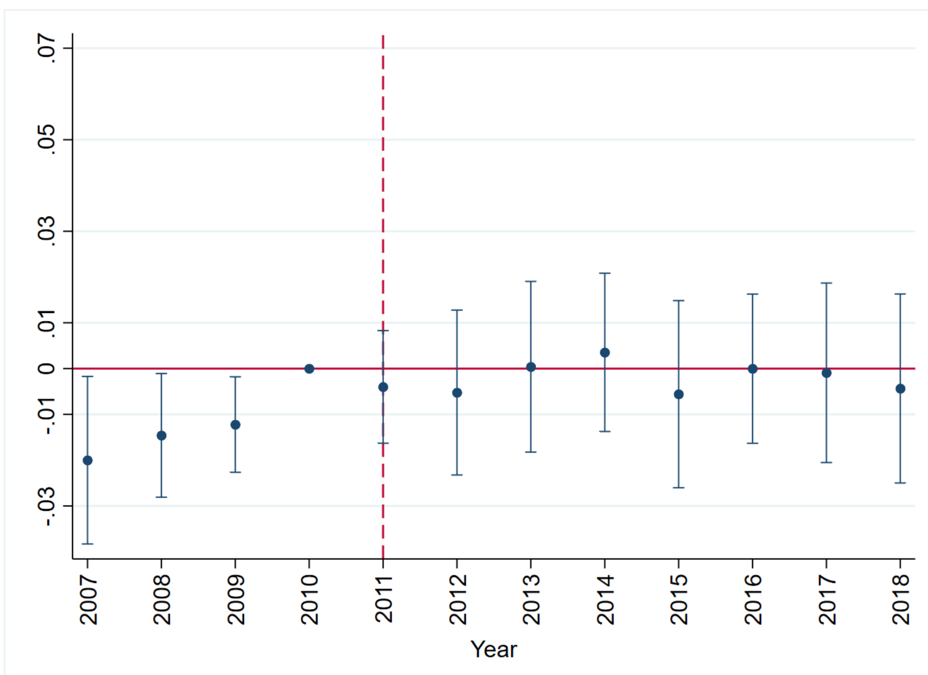
(d) ACF Productivity

Note: This figure plots the coefficients of difference-in-differences estimation. Four panels correspond to (a) log sales, (b) log number of employees, (c) labor productivity measures as sales divided by the number of employees, and (d) productivity estimated following the method of Ackerberg, Caves, and Frazer (2015). 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 1.C2. Log Number of Suppliers



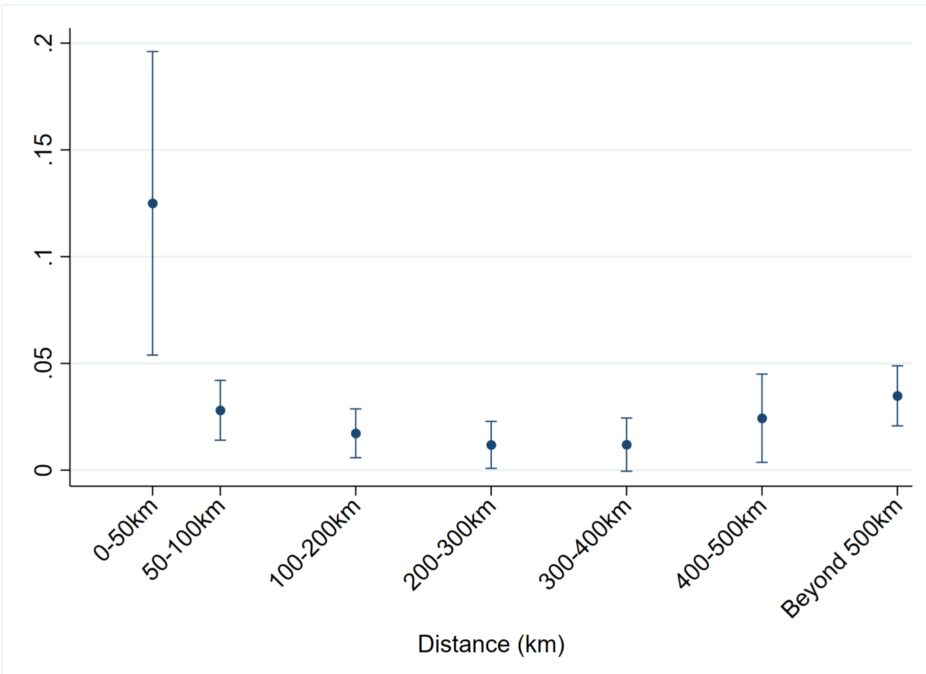
(a) The Number of Suppliers Outside



(b) Total Number of Suppliers

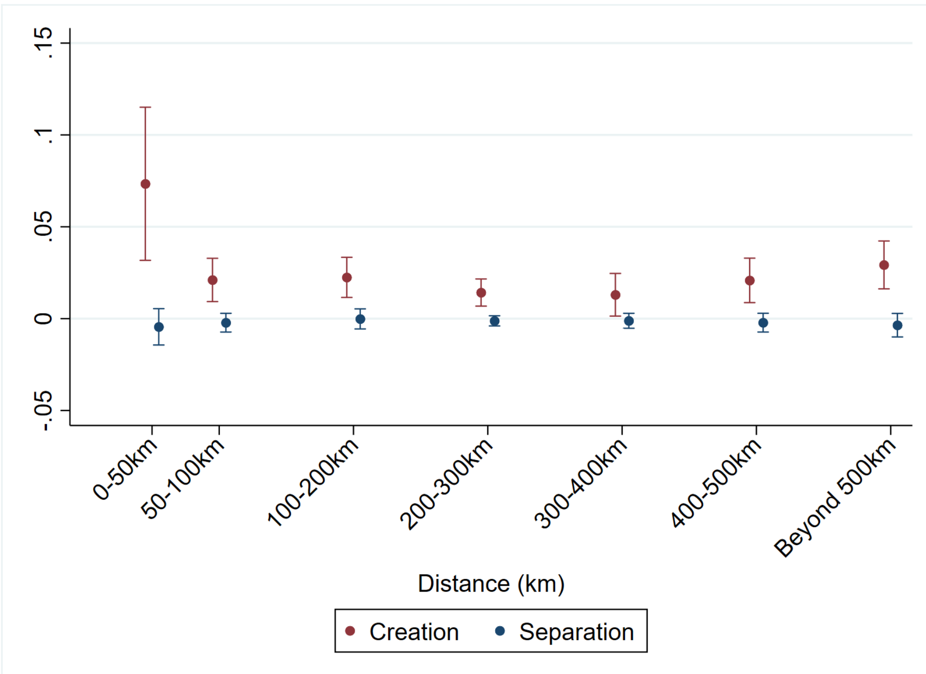
Note: These figures plot the coefficients of the event study design specification with (a) the log number of suppliers outside the disaster area, and (b) the log total number of suppliers as outcomes. The whiskers indicate the 95% confidence intervals based on the clustering in the 2-digit industry code and prefecture code, and the dots indicate the point estimates. The red vertical dotted line represents the year when the earthquake occurred.

Figure 1.C3. Log Number of Suppliers Within Distance Bands



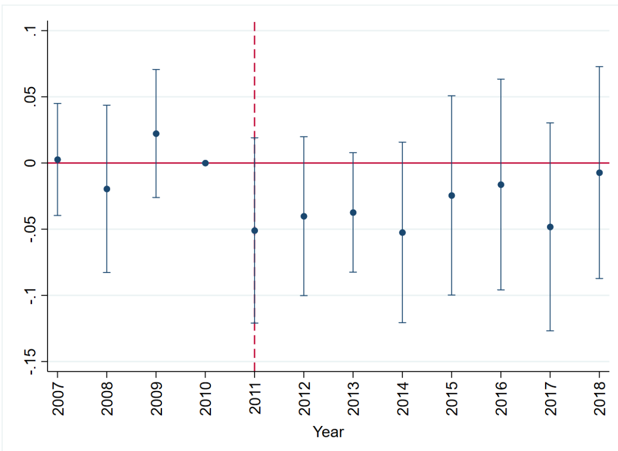
Note: This figure plots the coefficients of difference-in-differences estimation with the log numbers of suppliers within distance bands as outcomes. Excluding the disaster area, we split the rest of Japan into the following distance bands: 0–50 km, 50–100 km, 100–200 km, 200–300 km, 300–400 km, 400–500 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.

Figure 1.C4. Log Number of New and Dropped Suppliers Within Distance Bands

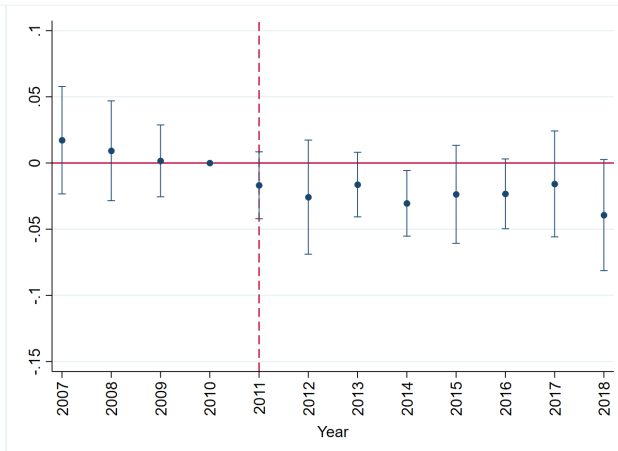


Note: This figure plots the coefficients of difference-in-differences estimation with the log numbers of new and dropped suppliers within distance bands as outcomes. Excluding the disaster area, we split the rest of Japan into seven distance bands: 0–50 km, 50–100 km, 100–200 km, 200–300 km, 300–400 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.

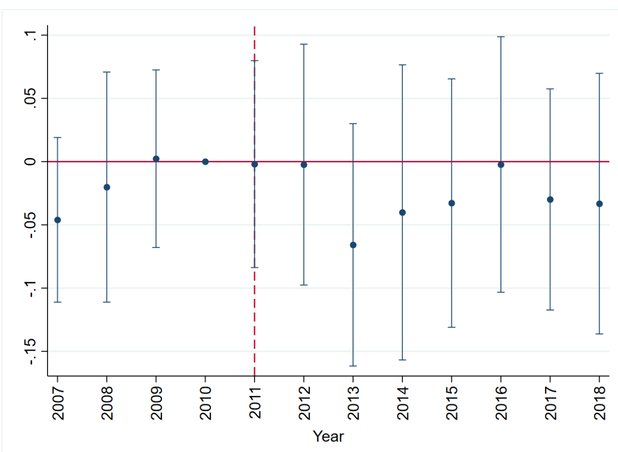
Figure 1.C5. Distance to Suppliers



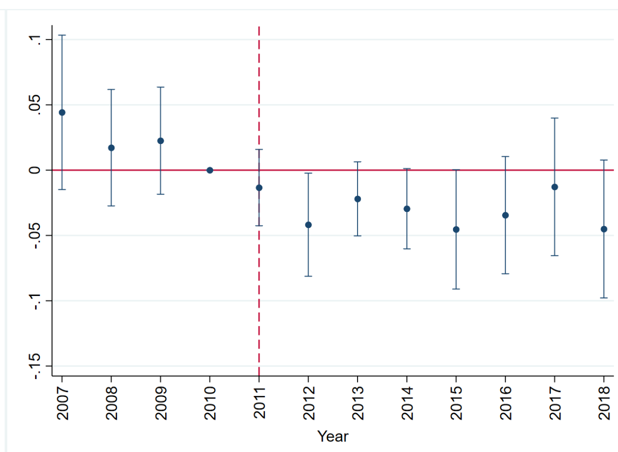
(a) Median Distance



(b) Maximum Distance



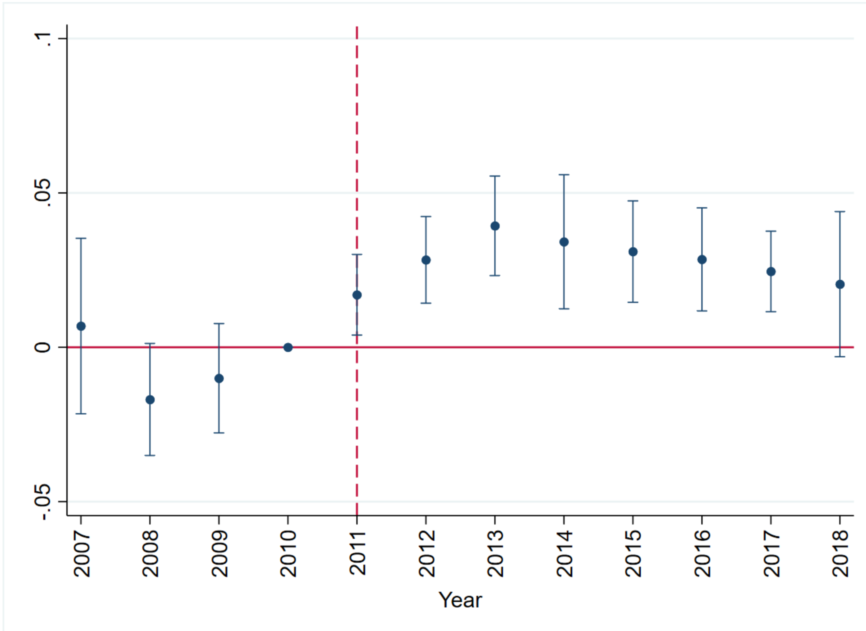
(c) Minimum Distance



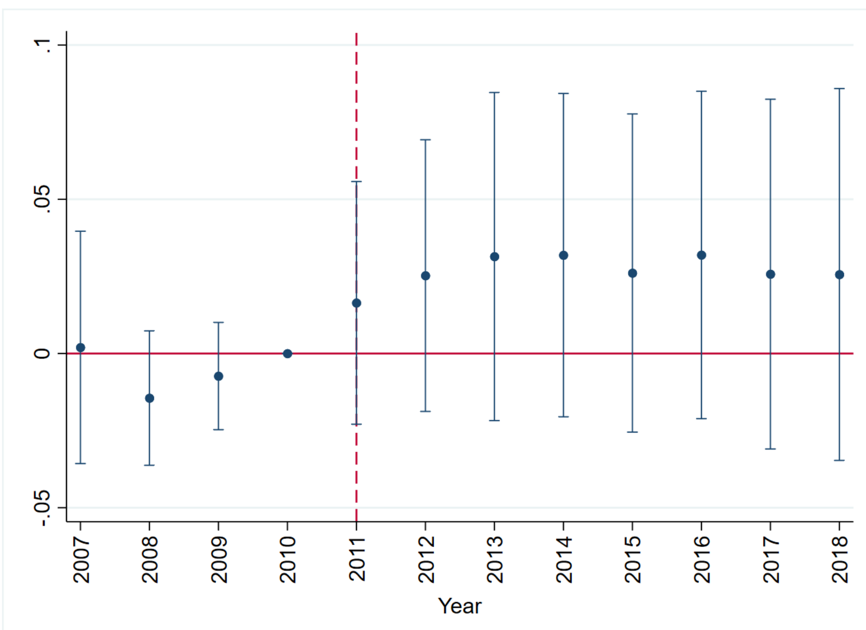
(d) SD of Distance

Note: This figure plots the coefficients of the event study design specification with the distance to suppliers as an outcome. We restrict the sample to those firms that lost at least one supplier inside the disaster area and added at least one supplier outside the disaster area between 2007–2010 and 2011–2014. Four panels correspond to median, maximum, minimum, and standard deviation of the distance. The whiskers indicate the 95% confidence intervals based on the clustering in 2-digit industry code and prefecture code, and the dots indicate the point estimates. The red vertical dotted line represents the year when the earthquake occurred.

Figure 1.C6. Share of Suppliers in the Same Regional Unit



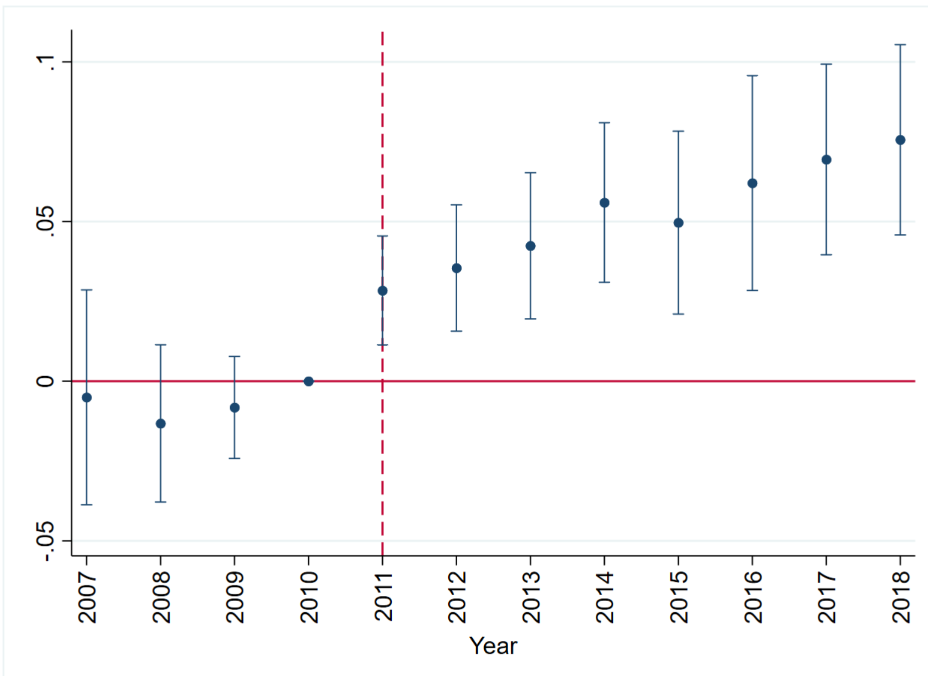
(a) Same Prefecture



(b) Same Region

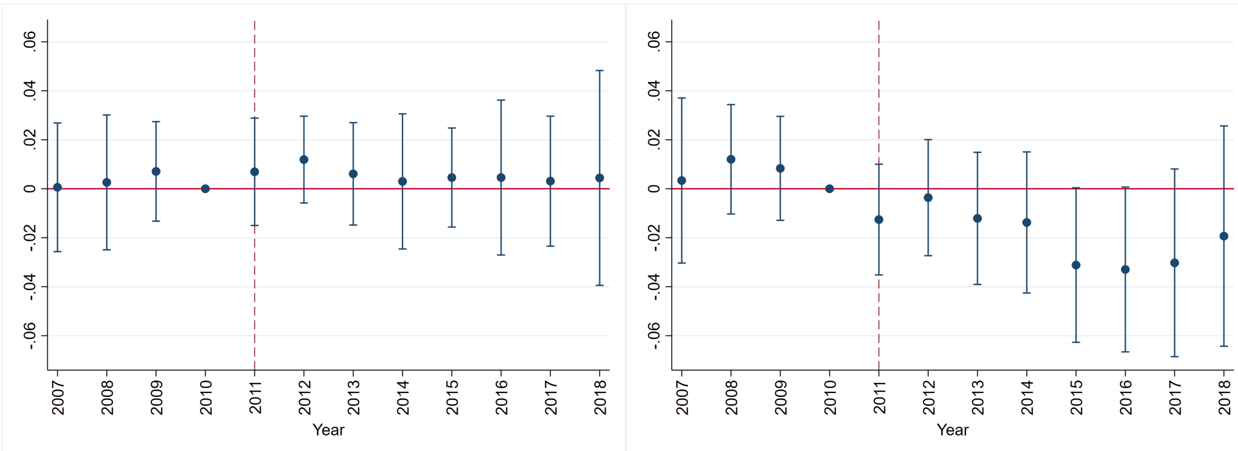
Note: This figure plots the coefficients of the event study design specification with the share of suppliers in the same regional unit as an outcome. We restrict the sample to those firms that lost at least one supplier inside the disaster area and added at least one supplier outside the disaster area between 2007–2010 and 2011–2014. Two panels correspond to the shares of suppliers in the same prefecture and that in the same region. The whiskers indicate the 95% confidence intervals based on the clustering in 2-digit industry code and prefecture code, and the dots indicate the point estimates. The red vertical dotted line represents the year when the earthquake occurred.

Figure 1.C7. Geographical Concentration



Note: This figure plots the coefficients of the event study design specification with the concentration measure as an outcome while restricting the sample to those firms that lost at least one supplier inside the disaster area and added at least one supplier outside the disaster area between 2007–2010 and 2011–2014. The whiskers indicate the 95% confidence intervals based on the clustering in 2-digit industry code and prefecture code, and the dots indicate the point estimates. The red vertical dotted line represents the year when the earthquake occurred.

Figure 1.C8. Log Sales: Duration of Relationships

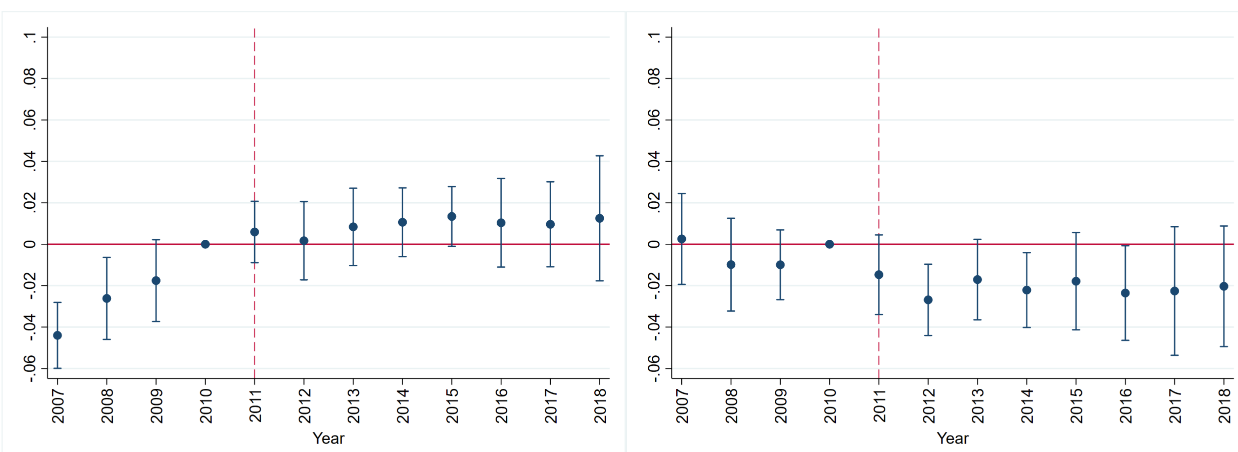


(a) Below Median

(b) Above Median

Note: This figure plots the coefficients of difference-in-differences estimation. Two panels use log sales as the outcome. Panal (a) corresponds to buyer firms that had relationships with suppliers inside the disaster area for more than three years, and Panel (b) corresponds to the rest of firms. 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 1.C9. Total Number of Suppliers: Duration of Relationships

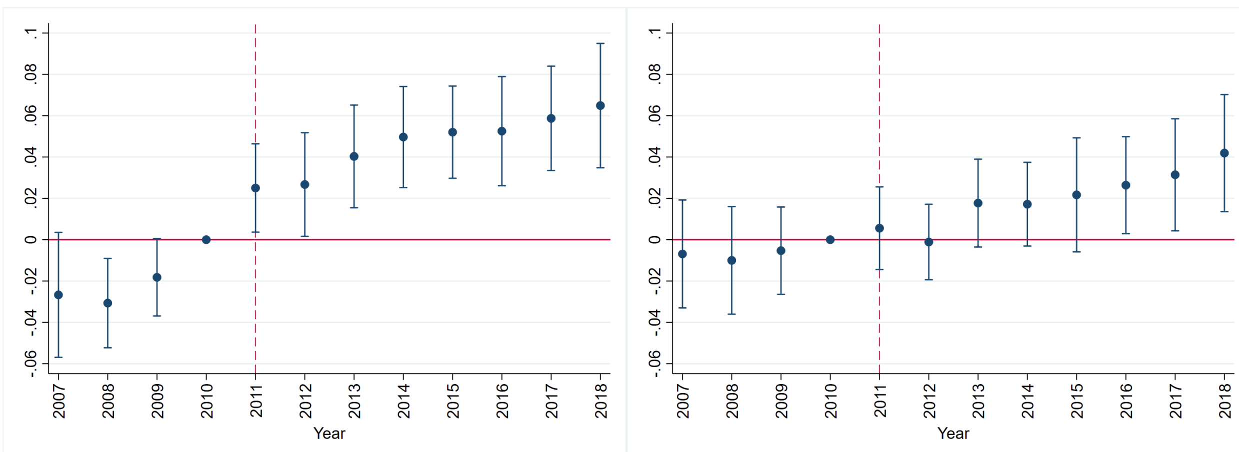


(a) Below Median

(b) Above Median

Note: This figure plots the coefficients of difference-in-differences estimation. Two panels use log total number of suppliers as the outcome. Panal (a) corresponds to buyer firms that had relationships with suppliers inside the disaster area for more than three years, and Panel (b) corresponds to the rest of firms. 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 1.C10. Number of Suppliers Outside: Duration of Relationships



(a) Below Median

(b) Above Median

Note: This figure plots the coefficients of difference-in-differences estimation. Two panels use log number of suppliers outside the disaster area as the outcome. Panal (a) corresponds to buyer firms that had relationships with suppliers inside the disaster area for more than three years, and Panel (b) corresponds to the rest of firms. 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.

Chapter 2

Theory and Evidence of Firm-to-firm Transaction Network Dynamics

2.1 Introduction

Production networks consist of individual firm activities and the interactions between them. Firms are inter-connected with each other to buy inputs from or sell outputs to other firms. It is widely acknowledged that the transaction network propagates the effects of economic shocks and policy changes. There is the growing literature on firm-to-firm transaction data. Most of these studies focus on the static aspect, whereas evidence is limited about the dynamic feature of the transaction network. Firms construct and reshape their networks through their growth trajectory. Successful firms can find trading partners while unsuccessful ones struggle to sell their products or acquire key inputs. Matching is essential for both parties involved in a transaction. Moreover, since firm-to-firm relationships comprise the economy-wide production networks, the churning of transaction relationships have substantial implications for aggregate productivity growth (Baqaee et al., 2023).

This study investigates firm-to-firm transaction network dynamics exploiting Japanese large-scale firm-level transaction relationship data. We first provide facts about dynamics of firm-to-firm transactions. Each year, we observe substantial churning in transaction network, even after controlling for firm exits. We also find evidence of productivity positive assortative matching between firms. High-productivity firms trade with similarly high-productivity firms while low-productivity firms get matched with low-productivity ones. Across periods, firms are more likely to keep trading with more productive firms and instead separate from less productive ones. Additionally, more productive firms start new transactions with more productive business partners. We then provide a theoretical framework to rationalize these findings, where supplier and customer firms are both heterogeneous in productivity. Supplier firms produce intermediate inputs and customer firms produce final goods. We assume monopolistic competition in both markets. With the relation-specific costs varying over productivity gap, we obtain positive assortative matching with a many-to-many matching framework.

Japanese large-scale firm-level transaction relationship data allow us to study how firms select and change their trading partners over time. A private credit reporting company, Tokyo Shoko Research (TSR), collects the information on firm-to-firm transactions on an annual basis. The data span between 2007 and 2018 and identify suppliers and customers, while values and products of transactions are not observable.

Our empirical analyses reveal the following three findings. First, we detect substantial churning in supply chains over time. Firms churn about 20% of their transaction partners every year, even after excluding the cases where either supplier or customer firms exit the market. We also estimate the average survival likelihood of a given firm-to-firm transaction and find that 80% of transactions disappear after about ten years.

Second, firm productivity is a key driver in matching between sellers and buyers. When a firm has higher productivity, the transaction is more likely to continue. Similarly, when a firm has lower productivity, the transaction is more likely to disappear. We also find that the productivity of new suppliers is higher than that of disappeared suppliers on average. We empirically find that productivity positive assortative matching exists between firms. The results also show that more productive customers trade with more productive suppliers. As a firm's own productivity increases, both the maximum and minimum productivity among its suppliers tend to increase.

Third, we develop a theoretical framework to rationalize the empirical findings about positive assortative matching in transaction network. We derive the implications for transaction network formation and its churning in response to productivity shocks. Firms choose their trading partners to maximize their profits, and the optimization problem results in sorting functions for both supplier and customer firms. Finally, we derive implications in the case of productivity shocks. The model is novel in that we derive positive assortative matching with a many-to-many matching framework.

This study contributes to the literature on firm-to-firm transaction network from both empirical and theoretical perspectives. First, this study adds to the recent literature which exploits firm-to-firm transaction data. Adao et al. (2020), Bernard et al. (2018), Dhyne et al. (2020), and Sugita et al. (2021) among others use the information on international trade to study firm-to-firm transactions. There is also a group of papers which focus on domestic firm-to-firm transactions. Atalay et al. (2011) and Lim (2018) use a proprietary dataset, Compustat. Alfaro-Ureña et al. (2022), Amiti et al. (2022), Bernard et al. (2022), Demir et al. (2021), Gadenne et al. (2020) and Panigrashi (2021) use tax administrative data to observe domestic transaction network.

This study is not the first to use Japanese large-scale firm-level transaction relationship data collected by Tokyo Shoko Research (TSR). This dataset has been explored in Bernard, Moxnes, and Saito (2019), Carvalho et al. (2021), Fujii, Saito, and Senga (2017), and Miyauchi (2021). However, the data used in this study is a twelve-year panel between 2007 and 2018, which is longer than the data used in the existing papers and therefore suited to study the dynamics of firm-to-firm transaction network. Those existing papers did not study endogenous network formation. We aim to fill this gap.

Imani and Ohyama (2022) leverage similar transaction relationship data from Teikoku Databank (TDB), another major credit reporting firm in Japan, and investigate the relationship between firm productivity, management and transaction relationships. Our research advances beyond their study in at least two dimensions. First, our study analyzes the characteristics of transaction partners as well as the dynamics of the transaction relationships. In particular, we empirically and theoretically investigate how the characteristics of newly created and separated partners interact with firm productivity. Second, our data surpass theirs in terms of the coverage of time and firm size. In terms of the time span, we use yearly panel data that span over a decade, whereas their data is cross-sectional. This results in that we have the advantage of employing fixed effects estimation, whereas they use a cross-sectional regression. Also, in terms of the sample coverage, the TSR data that we exploit include not only large firms but also a number of small and medium-sized ones, while the TDB data primarily consist of the sample of large firms. Therefore, our study offers more comprehensive analyses and provide insights into the dynamics of firm-to-firm transaction networks.

Second, this study contributes to the evidence and theory of firm-to-firm transaction network formation. Bernard and Moxnes (2018) provide a nice review of the literature. Among others, Bernard et al. (2018) and Sugita, Teshima, and Seira (2021) are the most relevant papers to our study. Bernard et al. (2018) construct a model with two-sided heterogeneity and derived sorting functions for trading partner choice. They show the lower bound of productivity required for the trading partner is decreasing in firm's own productivity. We extend the model to incorporate variable relationship-specific costs and show that there are both lower and upper bounds of productivity. With relationship specific costs increasing in productivity gap between trading partners, both bounds become increasing in firm's own productivity. Then, we show that positive assortative matching between firms exists within a many-to-many matching framework. Sugita, Teshima, and Seira (2021) focus on U.S.-Mexican trade and derive positive assortative matching. Our study differs from theirs in that our framework is many-to-many matching while their framework is one-to-one matching.

The rest of the chapter is structured as follows. Section 2 explains the data set, and Section 3 explains the basic facts on transaction network dynamics. Section 4 provides the theoretical framework to rationalize these findings. Section 5 concludes.

2.2 Data

2.2.1 Data

We exploit large-scale firm-to-firm transaction relationship data from Japan. The data source is 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 is not a census but close to comprehensive in that it covers about 70% of all incorporated firms in Japan, including both listed and non-listed ones. From the TSR data, we observe (i) firm-to-firm transaction relationships, (ii) basic firm characteristics including sales, employment, the number of establishments, the number of factories, 4-digit industry, geographical address, and (iii) balance sheet information, which allows us to observe firm-level inputs and outputs.

Firms are asked to report up to 48 partners (24 suppliers and 24 customers). Despite the cutoff, we can back up firm-to-firm transaction networks quite well by merging all reports from all firms in the survey. For example, a large firm usually has more than 48 partners, but by using reports from other firms, we can identify the trading partners for that firm. This gives us a comprehensive picture of Japanese firm-to-firm transaction network.

2.2.2 Summary Statistics

The dataset covers twelve years from 2007–2018. We restrict our sample to firms for which balance sheet information is available. Table 2.1 below shows summary statistics. The minimum numbers of suppliers and customers are zero, so the data include firms which exist most upstream and downstream in the supply chains.

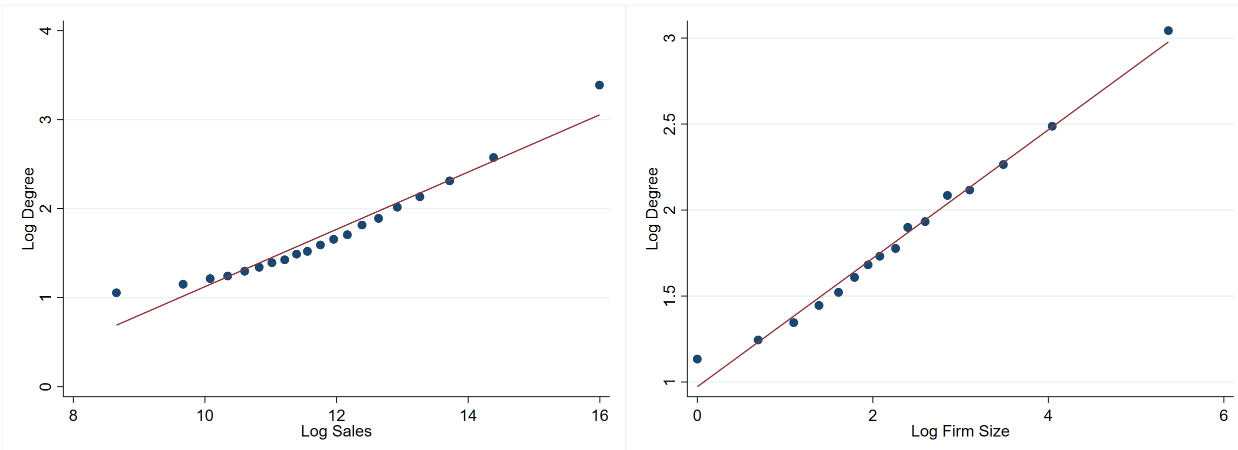
Table 2.1. Summary Statistics

	# of obs	mean	median	sd	max	min
Firm sales	1,313,842	3,264,482.249	242,560	67,415,218.959	12,201,443,328	58
Firm age	1,259,148	31.585	30	16.681	136	0
Firm size	1,313,842	48.997	10	590.224	200,601	1
Total # of links	1,313,842	16.959	8	81.502	8,647	1
# of suppliers	1,313,842	8.915	4	52.516	6,201	1
# of customers	1,313,842	8.044	3	43.153	6,259	0
Productivity	1,313,842	10.377	10.187	2.256	25.384	-1.555

Notes: Sales unit is 1,000 yen. Firm size is defined as the number of workers. Productivity refers to estimated Total Factor Productivity following Ackerberg, Caves, and Frazer (2015). We restrict our sample to firms for which productivity can be estimated.

Figure 2.1 below shows the relationships between the number of trading partners and firm characteristics. The left panel is for firm sales while the right panel is for firm size measured by the number of employees. Both panels show linear relationships, suggesting that larger firms in terms of higher sales or larger number of employees have more trading partners.

Figure 2.1. The Relationship Between Log Number of Links and Firm Characteristics



(a) Firm Sales

(b) Firm Size

Notes: This figure shows the relationship between the number of links and firm characteristics. The left panel is for firm sales while the right panel is for firm size measured by the number of employees.

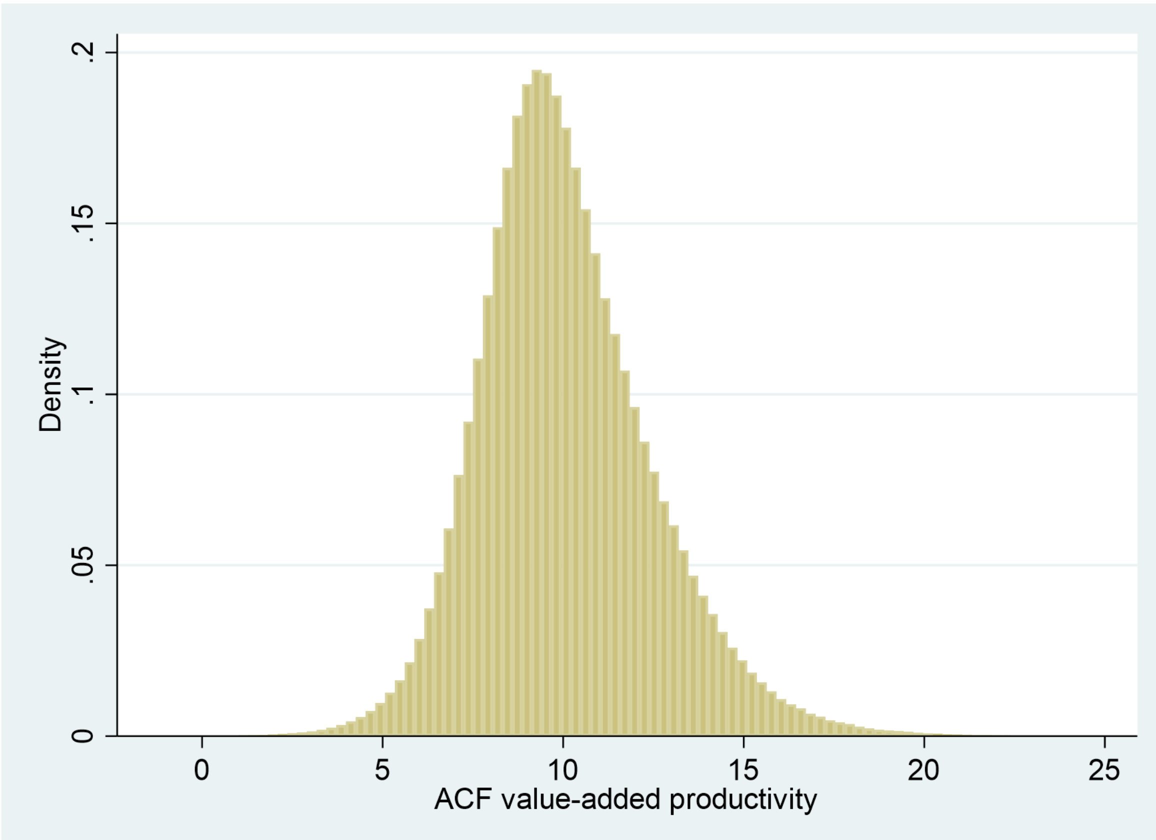
2.2.3 Estimating Productivity

Using balance sheet information, we estimate firm productivity following Ackerberg, Caves, and Frazer (2015). Figure 2.2 shows the histogram of estimated productivity. There is a mass of firms, but at the same time, productivity levels are dispersed across firms. It is also confirmed by the summary statistics for productivity shown in Table 2.1.

We restrict the sample to those firms which appear in the data for more than one year to investigate the churning behavior. This restriction is imposed for a conservative purpose, and should not alter the results.

We also use two different productivity measures for robustness checks. First, we demean the estimated productivity within the three-digit industry code. The purpose is to eliminate the industry-specific components of productivity levels. Second, we use labor productivity, defined as sales divided by the number of employees. As not all firms report balance sheet information, this measure gives a larger number of observations. We exploit these two measures as robustness checks for the main findings.

Figure 2.2. Histogram of Productivity



Notes: This figure shows the histogram of productivity obtained by the ACF value-added productivity estimation method.

2.2.4 Network Dynamics

Table 2.2 below shows the summary of the firm-to-firm transaction network. Panel A shows the static patterns of the network. The average number of suppliers for firms is 7.451, and that of customers is 7.287. Panel B shows the dynamic patterns of the network. The average probability of continuing transactions between two consecutive years is 0.800; conversely, the probability that it terminates from a year to the next is 0.200. The average probability of starting a new transaction with a new trading partner is 0.126. This implies that firms churn about 20% of their transaction partners every year. The probability of separation and that of creation do not sum up to be one because the denominators are different.

In Figure 2.3, we plot the survival function of firm-to-firm transactions by using the Kaplan-Meier estimator. The horizontal axis represents the time variable expressed in years. All transactions existing in 2007 start at the top of the vertical axis, which indicates the proportion that has not experienced a separating event. The horizontal axis represents the survival time (in years) of each interval, and the vertical distance between the lines corresponds to the change in cumulative probabilities. Thus, a decline in the plot is associated with a separating event. Note that the separation is the largest in the first year and gradually gets smaller over time. We can see that half of the initial transactions disappear in about 4 years and that in 10 years, about 20% of initial transactions remain.

Table 2.2. Network Dynamics

Panel A: Static Patterns	
Average number of suppliers	7.451
Average number of customers	7.287
Panel B: Dynamic Patterns	
Average probability of continuing links	0.800
Average probability of separating links	0.200
Average probability of creating new links	0.126

Notes: Panel A shows the static patterns of firm-to-firm transactions. Panel B shows the dynamic patterns. "Average probability of continuing links" indicates the percentage of transactions existing in period t that remain in period $t+1$. "Average probability of separating links" indicates the percentage of transactions existing in period t that are disappeared at $t+1$. "Average probability of creating new links" represents the percentage of transactions that did not exist in period t among those that existed in period $t+1$.

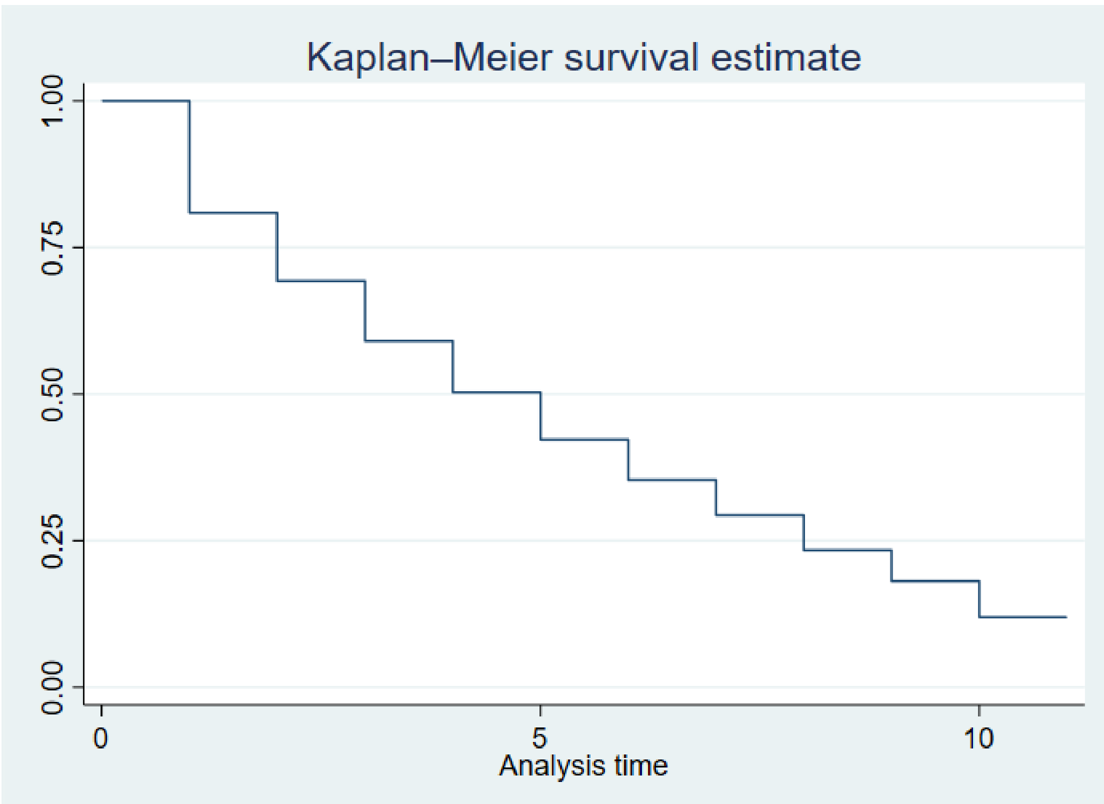
2.3 Empirical Results

2.3.1 Graphical Evidence

Here, we examine the feature of endogenous network formation. In particular, we look for empirical evidence for the presence of positive assortative matching or negative assortative matching between firms.

First, we divide the transaction into three types: (i) continued transaction, (ii) separated transaction, and (iii) newly created transaction between years t to $t+1$. With revealed preference, continued transactions as well as newly created transactions should be more preferable to separated ones. Figure 2.4 plots three productivity distributions for different groups. Continuation corresponds to the group of supplier firms with which customer firms

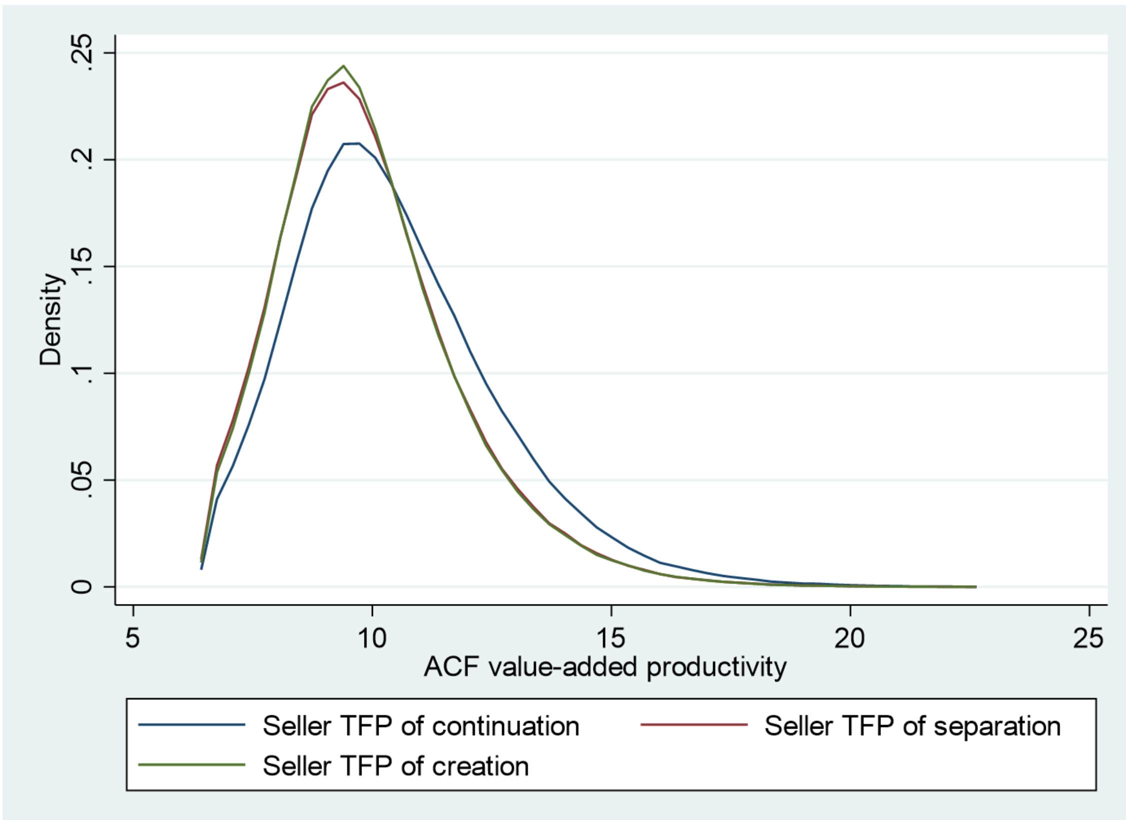
Figure 2.3. Survival Share of Transactions



Notes: This figure plots the Kaplan-Meier survival estimates of firm-to-firm transactions that existed in 2007. The length of the horizontal line represents the survival time (in years) of each interval, and the vertical distance between the horizontal lines corresponds to the change in cumulative probability as the curve moves to the right.

continued to trade. Separation corresponds to the group of supplier firms with which customer firms stopped trading. Lastly, creation corresponds to the group of supplier firms with which customer firms newly started trading.

Figure 2.4. Distributions of Productivity



Notes: This figure plots the distribution of supplier productivity for each of continued, separated and created transactions by customer firms.

The productivity distribution for continued transactions is the most to the right as expected, but that for newly created transactions differs little from that for separated transactions. This observation can be explained as follows. Created transactions do not necessarily occur when a firm's own productivity increases and is matched with a more productive counterpart. Matching can also happen when a firm's own productivity is lowered and is matched with a less productive counterpart. A similar argument can be made for separated transactions. We interpret that the productivity distributions is closer for the created and separated transactions because of the mixture of these downward and upward matching patterns.

2.3.2 Reduced-form Evidence

Next, we run the following regression to further examine the assortativity of the firm-to-firm transaction network. In order to study how the set of trading partners changes depending on firm i's productivity, we run the following regression:

$$Y_{it} = \beta \text{Productivity}_{it} + X_{it}\gamma + \eta_i + \tau_{jkt} + \epsilon_{it} \tag{8}$$

where Productivity_{it} is firm i's productivity level in year t and X_{it} refers to firm covariates including firm age and size. We also include firm fixed effects, η_i, and industry-prefecture-year fixed effects, τ_{jkt}.

For outcome, Y_{it}, we use the maximum and minimum productivity among firm i's suppliers. Suppose that a firm i has five suppliers in year t, and the productivity of each supplier can be ordered as $z_1 \leq z_2 \leq z_3 \leq z_4 \leq z_5$. Then, the maximum productivity is z_5, and the minimum productivity is z_1.

The moments would rise as firm i's productivity increases when there exists positive assortative matching. That is because that if a firm becomes more productive, then (i) it starts to trade with more productive supplier that it was not able to reach, and (ii) the productivity of the least productive suppliers increases as well. The opposite should be the case for negative assortative matching.

Table 2.3. Productivity Positive Assortative Matching: Maximum and Minimum

	Maximum		**Minimum**	
	(1)	(2)	(3)	(4)
Own Productivity	0.0152***	0.0148***	0.00383*	0.00689***
	(0.00107)	(0.00110)	(0.00216)	(0.00227)
Covariates		x		x
Firm FE	x	x	x	x
Other FEs	x	x	x	x
Observations	1,220,811	1,172,061	1,220,811	1,172,061
R-squared	0.969	0.967	0.791	0.788
Mean of Dep.Var.	16.61	16.77	10.15	10.12

Notes: Robust standard errors clustered at the level of the firm in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) show the results when we take the maximum supplier productivity as the outcome, and columns (3) and (4) show the results when we take the minimum supplier productivity as the outcome. Columns (2) and (4) control for the log firm age and the log the number of workers as the covariates.

Table 2.3 shows the regression results with maximum and minimum productivities among suppliers as the outcomes. Columns (1) and (2) use the maximum productivity as the outcome, and columns (3) and (4) use the minimum productivity. All columns show the results with firm fixed effects. Columns (2) and (4) add firm covariates as independent variables.

We obtain positive and statistically significant estimates. The results show that maximum and minimum productivities among suppliers are increasing in firm's own productivity, even after controlling for firm characteristics and including fixed effects. First, as a firm becomes more productive, it starts to trade with even more productive supplier, and the upper bound of supplier's productivity increases. Second, it ceases to trade with the least productive supplier, and the lower bound of supplier's productivity increases. This set of findings imply that there exists positive assortative matching.[23]

Nest, we use mean and standard deviation of the productivity among suppliers as the outcomes. Table 2.4 shows the regression results. Columns (1) and (2) use the mean productivity, and columns (3) and (4) use the standard deviation of the productivity among suppliers. The results confirm the existence of positive assortative matching.

Table 2.4. Productivity Positive Assortative Matching: Mean and Standard Deviation

	Mean		**Standard Deviation**	
	(1)	(2)	(3)	(4)
Own Productivity	0.00455***	0.00596***	-0.00341***	-0.00330***
	(0.00114)	(0.00119)	(0.000986)	(0.00106)
Covariates		x		x
Firm FE	x	x	x	x
Other FEs	x	x	x	x
Observations	1,220,811	1,172,061	1,029,885	964,976
R-squared	0.927	0.926	0.810	0.811
Mean of Dep.Var.	13.17	13.24	2.891	2.898

Notes: Robust standard errors clustered at the level of the firm in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) show the results when we take the maximum supplier productivity as the outcome, and columns (3) and (4) show the results when we take the minimum supplier productivity as the outcome. Columns (2) and (4) control for the log firm age and the log the number of workers as the covariates.

The mean productivity is increasing in firm's own productivity. Notably, the standard deviation of the suppliers' productivities is decreasing in own productivity. This reveals the

[23] The results of positive assortative matching are related to many theoretical studies on labor and marriage markets (e.g., Becker 1973; Shimer, and Smith 2000). For theoretical surveys, see, for example, Petrongolo, and Pissarides (2001) and Chade, Eeckhout, and Smith (2017).

selection mechanism of trading partners. As a firm becomes more productive, its suppliers become more similar in terms of productivity.

We have conducted several robustness checks, which further confirm our findings. Tables 2.A1 and 2.A2 show the estimation results when we use demeaned ACF productivity within three-digit industry code for the outcomes and own productivity. Tables 2.A3 and 2.A4 show the estimation results when we use labor productivity defined as sales per employee for the outcomes and own productivity.

Although the baseline estimation uses the entire sample period from 2007–2018, we have conducted a robustness check by restricting to 2007–2010. The supply chain shocks caused by the 2011 Great East Japan Earthquake have affected firms' choice of trading partners and may have further altered the positive assortativity of the firm-to-firm transaction network. The results are shown in Tables 2.A5 through 2.A10. Tables 2.A5 and 2.A6 show the estimation results when we use ACF productivity, Tables 2.A7 and 2.A8 show the results when we use industry-demeaned productivity, and Tables 2.A9 and 2.A10 show the results when we use labor productivity. All of these further support the results of productivity positive assortative matching.

2.4 Theoretical Framework

We provide a theoretical framework to rationalize the findings of positive assortative matching. As in Bernard et al. (2018), we suppose that both supplier and customer firms are heterogeneous in productivity and compete in monopolistic competition. Supplier firms provide differentiated intermediate inputs, and customer firms produce differentiated final goods. We denote the elasticity of substitution as $\sigma > 1$; it is identical for both intermediates and final goods.

A supplier firm has productivity z, which follows the Pareto distribution: $z \sim F(z) = 1 - z^{-\gamma}$. A customer firm has productivity Z, which also follows the Pareto distribution: $Z \sim G(Z) = 1 - Z^{-\Gamma}$. We impose $\Gamma > \gamma > \sigma - 1$ so that the price index for final goods is finite.

We incorporate the variable relationship-specific cost $f(z, Z)$, which is dependent on productivity levels of both supplier and customer firms as follows:

$$
\begin{aligned}
\frac{\partial f}{\partial z} &> 0 \quad \text{if } z > Z \\
\frac{\partial f}{\partial Z} &> 0 \quad \text{if } Z > z \\
\frac{\partial^2 f}{\partial z \partial Z} &< 0 \quad \forall z \ \forall Z
\end{aligned}
$$

This is in contrast to Bernard et al. (2018), which assume the fixed cost for a transaction between a supplier and a customer firm. Here, we assume that the relationship-specific cost is increasing in productivity gap between supplier and customer, and decreases when both firms simultaneously get more productive. This is intuitive as a more productive firm would search for better partners if the existing partners are not well matched in that their productivity levels are far from each other.

Both intermediates and final goods markets are characterized by monopolistic competition. Intermediates producers (suppliers) have the pricing rule

$$p(z) = \frac{\sigma}{\sigma - 1}\frac{w}{z} \tag{9}$$

Similarly, final goods producers (customers) have the pricing rule

$$P(Z) = \frac{\sigma}{\sigma - 1}\frac{q(Z)}{Z}, \tag{10}$$

where $q(Z)$ is the ideal price index for intermediate inputs. A customer firm with Z trade with sellers with $z \in [\underline{z}, \bar{z}]$ so that

$$q(Z)^{1-\sigma} \quad = \quad \int_{\underline{z}}^{\bar{z}} p(z)^{1-\sigma} dF(z)$$

The sales of intermediates by an intermediates producer (seller) z to a final goods producer (buyer) Z becomes

$$r(z, Z) = \left(\frac{p(z)}{q(Z)}\right)^{1-\sigma} E(z) \tag{11}$$

where $E(Z)$ is total spending on intermediates by a final goods producer Z. Then, an intermediate firm's net profits from a (z, Z) match is

$$\Pi(z, Z) = \frac{r(z, Z)}{\sigma} - wf(z, Z) \tag{12}$$

The upper and lower bounds are derived from zero cutoff profit conditions, as in Melitz (2003). Zero cutoff profit condition for seller with the lower bound of productivity for buyers $\underline{Z}$: $\Pi(z, \underline{Z}) = 0$

$$q(\underline{Z})^{\sigma-1} E(\underline{Z}) = \sigma w f(z, \underline{Z}) \left(\frac{\sigma}{\sigma - 1} w\right)^{\sigma-1} z^{1-\sigma} \tag{13}$$

Zero cutoff profit condition for seller with the upper bound of productivity for buyers $\bar{Z}$: $\Pi(z, \bar{Z}) = 0$

$$q(\bar{Z})^{\sigma-1} E(\bar{Z}) = \sigma w f(z, \bar{Z}) \left(\frac{\sigma}{\sigma - 1} w \right)^{\sigma-1} z^{1-\sigma} \tag{14}$$

Combining these, we obtain solutions for the sorting functions, $\underline{z}(Z)$ and $\bar{z}(Z)$. It can be shown that both are increasing in Z. Both lower and upper bounds of the matched supplier is increasing in customer firm's own productivity. This implies that productivity positive assortative matching exists.

Proposition 1. *Suppose there are two buyer firms with different productivity levels ($Z_1 < Z_2$), respectively. Then, the matched set of seller firms is $[\underline{z}(Z_1),\ \bar{z}(Z_1)]$ for Z_1 buyer and is $[\underline{z}(Z_2),\ \bar{z}(Z_2)]$ for Z_2 buyer. Then, since we have $\partial \underline{z}(Z)/\partial Z > 0$ and $\partial \bar{z}(Z)/\partial Z > 0$, we get*

$$\underline{z}(Z_1) < \underline{z}(Z_2)$$
$$\bar{z}(Z_1) < \bar{z}(Z_2)$$

i.e., productivity positive assortative matching property between buyer and seller firms.

This framework brings transaction network churning when there comes productivity shocks. The original set of matches divides into continuation and separation, and new matches are created. Proposition 2 looks at productivity shock on the seller side while Proposition 3 focuses on the buyer side.

Proposition 2. *Fix seller productivity at z. Suppose that there is positive productivity shock on the buyer such that productivity improves from Z to $Z + \Delta$, with Δ¿0. Then, the match continues if seller productivity $z \sim [\underline{z}(Z + \Delta),\ \bar{z}(Z)]$ while it separates if seller productivity $z \sim [\underline{z}(Z),\ \underline{z}(Z+\Delta)]$. Additionally, the new match is created if seller productivity $z \sim [\bar{z}(Z),\ \bar{z}(Z + \Delta)]$.*

Proposition 3. *Fix buyer productivity at Z. Suppose that there is positive productivity shock on the seller such that productivity improves from z to $z + \delta$, with δ¿0. Then, the match continues if seller productivity $\underline{z}(Z) < z < z + \delta < \bar{z}(Z)$ while it separates if seller productivity $z < \bar{z}(Z) < z + \delta$. Additionally, the new match is created if seller productivity $z < \underline{z}(Z) < z + \delta$.*

These theoretical implications allow us to study how firms would churn their transaction networks due to productivity shocks. This work contributes to the existing literature in that we incorporated a many-to-many matching framework and that we derived the upper and lower bounds of the matched set between firms.

2.5 Conclusion

This study contributes to the vibrant discussion of the firm-to-firm transaction network by exploiting Japanese large-scale firm-level transaction relationship data between 2007 and 2018. Adding to the existing literature, we focus on the dynamic aspect of the network and analyze the relationship between firm-to-firm transaction dynamics and firm characteristics. First, we provide basic facts about positive assortative matching between firms. We find that more productive firms are more likely to trade with similarly more productive firms. This occurs not just in each time period but also across times in that more productive firms are more likely to keep trading with more productive ones while they are more likely to stop trading with less productive ones. Second, we build a theoretical framework to rationalize these findings with a many-to-many matching framework. The model allows us to derive separate implications in the case of productivity shocks coming from suppliers or customers. A promising area of future research is to study the relationship between firm-to-firm matching and aggregate economic growth and what policies could promote growth exploiting transaction network.

Acknowledgement

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2.6 Reference

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Appendix A Tables and Figures

Tables 2.A1 and 2.A2 show the estimation results when we use demeaned ACF productivity within three-digit industry code for the outcomes and own productivity. Tables 2.A3 and 2.A4 show the estimation results when we use labor productivity defined as sales per employee for the outcomes and own productivity.

Although the baseline estimation uses data from 2007-2018, the supply chain shocks caused by the 2011 Great East Japan Earthquake may have affected firms' choice of trading partners. Therefore, as a robustness check, we estimated using data from 2007–2010, and the results are shown in Tables 2.A5 through 2.A10. Tables 2.A5 and 2.A6 show the estimation results when we use ACF productivity, Tables 2.A7 and 2.A8 show the results when we use industry-demeaned productivity, and Tables 2.A9 and 2.A10 show the results when we use labor productivity.

Table 2.A1. Demeaned Productivity Positive Assortative Matching: Maximum and Minimum

	Maximum		**Minimum**	
	(1)	(2)	(3)	(4)
Own Productivity	0.00640***	0.00504***	0.00358*	0.00630***
	(0.00106)	(0.00109)	(0.00190)	(0.00199)
Covariates		x		x
Firm FE	x	x	x	x
Other FEs	x	x	x	x
Observations	1,220,811	1,172,061	1,220,811	1,172,061
R-squared	0.958	0.957	0.757	0.755
Mean of Dep.Var.	5.282	5.414	-0.401	-0.421

Notes: Robust standard errors clustered at the level of the firm in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) show the results when we take the maximum supplier productivity as the outcome, and columns (3) and (4) show the results when we take the minimum supplier productivity as the outcome. Columns (2) and (4) control for the log of firm age and the log of the number of workers as the covariates.

Table 2.A2. Demeaned Productivity Positive Assortative Matching: Mean and Standard Deviation

	Mean		**Standard Deviation**	
	(1)	(2)	(3)	(4)
Own Productivity	0.00361***	0.00449***	-0.00618***	-0.00590***
	(0.00100)	(0.00105)	(0.000893)	(0.000956)
Covariates		x		x
Firm FE	x	x	x	x
Other FEs	x	x	x	x
Observations	1,220,811	1,172,061	1,029,885	964,976
R-squared	0.907	0.905	0.802	0.803
Mean of Dep.Var.	2.271	2.321	2.499	2.506

Notes: Robust standard errors clustered at the level of the firm in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) show the results when we take the maximum supplier productivity as the outcome, and columns (3) and (4) show the results when we take the minimum supplier productivity as the outcome. Columns (2) and (4) control for the log of firm age and the log of the number of workers as the covariates.

Table 2.A3. Labor Productivity Positive Assortative Matching: Maximum and Minimum

	Maximum		**Minimum**	
	(1)	(2)	(3)	(4)
Own Productivity	0.00588	0.00581	0.000980*	0.000977*
	(0.00376)	(0.00373)	(0.00190)	(0.00199)
Covariates		x		x
Firm FE	x	x	x	x
Other FEs	x	x	x	x
Observations	6,100,451	5,608,656	6,100,451	5,608,656
R-squared	0.859	0.861	0.809	0.812
Mean of Dep.Var.	308,756	323,511	40,751	39,444

Notes: Robust standard errors clustered at the level of the firm in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) show the results when we take the maximum supplier productivity as the outcome, and columns (3) and (4) show the results when we take the minimum supplier productivity as the outcome. Columns (2) and (4) control for the log of firm age as the covariate.

Table 2.A4. Labor Productivity Positive Assortative Matching: Mean and Standard Deviation

	Mean		**Standard Deviation**	
	(1)	(2)	(3)	(4)
Own Productivity	0.00143**	0.00141**	0.00143**	0.00141**
	(0.000712)	(0.000704)	(0.000712)	(0.000704)
Covariates		x		x
Firm FE	x	x	x	x
Other FEs	x	x	x	x
Observations	6,100,451	5,608,656	6,100,451	5,608,656
R-squared	0.866	0.870	0.866	0.870
Mean of Dep.Var.	109,227	111,025	109,227	111,025

Notes: Robust standard errors clustered at the level of the firm in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) show the results when we take the maximum supplier productivity as the outcome, and columns (3) and (4) show the results when we take the minimum supplier productivity as the outcome. Columns (2) and (4) control for the log of firm age as the covariate.

Table 2.A5. Productivity Positive Assortative Matching: Maximum and Minimum, 2007–2010

	Maximum		**Minimum**	
	(1)	(2)	(3)	(4)
Own Productivity	0.00963***	0.00955***	0.00864*	0.0108**
	(0.00187)	(0.00192)	(0.00511)	(0.00529)
Covariates		x		x
Firm FE	x	x	x	x
Other FEs	x	x	x	x
Observations	254,839	247,540	254,839	247,540
R-squared	0.981	0.981	0.822	0.821
Mean of Dep.Var.	17.33	17.46	10.09	10.07

Notes: Robust standard errors clustered at the level of the firm in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) show the results when we take the maximum supplier productivity as the outcome, and columns (3) and (4) show the results when we take the minimum supplier productivity as the outcome. Columns (2) and (4) control for the log of firm age and the log of the number of workers as the covariates.

Table 2.A6. Productivity Positive Assortative Matching: Mean and Standard Deviation, 2007–2010

	Mean		**Standard Deviation**	
	(1)	(2)	(3)	(4)
Own Productivity	0.00542**	0.00600**	-0.00628***	-0.00685***
	(0.00251)	(0.00259)	(0.00207)	(0.00212)
Covariates		x		x
Firm FE	x	x	x	x
Other FEs	x	x	x	x
Observations	254,839	247,540	228,562	224,584
R-squared	0.942	0.942	0.850	0.849
Mean of Dep.Var.	13.51	13.56	2.999	3.009

Notes: Robust standard errors clustered at the level of the firm in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) show the results when we take the maximum supplier productivity as the outcome, and columns (3) and (4) show the results when we take the minimum supplier productivity as the outcome. Columns (2) and (4) control for the log of firm age and the log of the number of workers as the covariates.

Table 2.A7. Demeaned Productivity Positive Assortative Matching: Maximum and Minimum, 2007–2010

	Maximum		**Minimum**	
	(1)	(2)	(3)	(4)
Own Productivity	0.00930***	0.00939***	0.00791*	0.0103**
	(0.00193)	(0.00198)	(0.00446)	(0.00461)
Covariates		x		x
Firm FE	x	x	x	x
Other FEs	x	x	x	x
Observations	254,839	247,540	254,839	247,540
R-squared	0.973	0.972	0.793	0.791
Mean of Dep.Var.	5.800	5.900	-0.596	-0.617

Notes: Robust standard errors clustered at the level of the firm in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) show the results when we take the maximum supplier productivity as the outcome, and columns (3) and (4) show the results when we take the minimum supplier productivity as the outcome. Columns (2) and (4) control for the log of firm age and the log of the number of workers as the covariates.

Table 2.A8. Demeaned Productivity Positive Assortative Matching: Mean and Standard Deviation, 2007–2010

	Mean		**Standard Deviation**	
	(1)	(2)	(3)	(4)
Own Productivity	0.00821***	0.00907***	-0.00466**	-0.00518***
	(0.00219)	(0.00225)	(0.00185)	(0.00189)
Covariates		x		x
Firm FE	x	x	x	x
Other FEs	x	x	x	x
Observations	254,839	247,540	228,562	224,584
R-squared	0.924	0.923	0.846	0.845
Mean of Dep.Var.	2.423	2.458	2.617	2.626

Notes: Robust standard errors clustered at the level of the firm in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) show the results when we take the maximum supplier productivity as the outcome, and columns (3) and (4) show the results when we take the minimum supplier productivity as the outcome. Columns (2) and (4) control for the log of firm age and the log of the number of workers as the covariates.

Table 2.A9. Labor Productivity Positive Assortative Matching: Maximum and Minimum, 2007–2010

	Maximum		**Minimum**	
	(1)	(2)	(3)	(4)
Own Productivity	0.0260*	0.0257*	0.00145*	0.00145*
	(0.0153)	(0.0152)	(0.000743)	(0.000744)
Covariates		x		x
Firm FE	x	x	x	x
Other FEs	x	x	x	x
Observations	2,039,208	1,880,467	2,039,208	1,880,467
R-squared	0.935	0.935	0.864	0.863
Mean of Dep.Var.	331,272	346,955	40,068	38,982

Notes: Robust standard errors clustered at the level of the firm in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) show the results when we take the maximum supplier productivity as the outcome, and columns (3) and (4) show the results when we take the minimum supplier productivity as the outcome. Columns (2) and (4) control for the log of firm age and the log of the number of workers as the covariates.

Table 2.A10. Labor Productivity Positive Assortative Matching: Mean and Standard Deviation, 2007–2010

	Mean		**Standard Deviation**	
	(1)	(2)	(3)	(4)
Own Productivity	0.00457**	0.00451**	0.00808**	0.00793**
	(0.00192)	(0.00190)	(0.00356)	(0.00355)
Covariates		x		x
Firm FE	x	x	x	x
Other FEs	x	x	x	x
Observations	2,039,208	1,880,467	1,695,767	1,589,930
R-squared	0.935	0.935	0.945	0.945
Mean of Dep.Var.	113,761	115,875	135,860	140,227

Notes: Robust standard errors clustered at the level of the firm in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) show the results when we take the maximum supplier productivity as the outcome, and columns (3) and (4) show the results when we take the minimum supplier productivity as the outcome. Columns (2) and (4) control for the log of firm age and the log of the number of workers as the covariates.

Chapter 3

Do Well Managed Firms Make Better Forecasts?

3.1 Introduction

The sagacious business man represents the other extreme; he is constantly forecasting. Many great corporations, banks, and investment trusts today maintain statistical departments largely for the purpose of gauging the future developments of business. The carefully calculated forecasts made by these and independent services tend to reduce the element of risk, and to aid intelligent speculation.

Irving Fisher (1930)

Economic success and the managerial ability to accurately forecast future conditions may be strongly related, as sadly illustrated by Fisher himself, who lost his fortune after the 1929 stock market crash. It is likely this anecdote generalises: errors in estimates about future economic conditions will lead firms to make many inferior decisions such as mis-timed investments or lost sales opportunities.[24]

In this study, we test this idea directly by taking data from the new Management and Expectations Survey (hereafter, MES) that we designed and was executed by the UK Office for National Statistics (ONS). We document a new set of empirical facts on the relationship between firm performance and management practices, looking not just at forecasts and outcomes at the level of the firm, but also at their forecasting ability over macroeconomic variables such as GDP. The major novelty of this study is in the measurement of a firm's ability to forecast future outcomes (both macro objects like GDP and micro objects such as its own turnover) that have a bearing on their ability to make good business decisions. By exploiting cross-sectional differences in the accuracy of forecasting both macro- and micro-level outcomes, we robustly isolate the role of management capabilities in driving performance differences across firms. Combined with quantitative management scores, and a battery of additional firm-level control variables obtained from ONS micro-data (both MES

[24]It has been known that judgement errors in estimates of business cases are pervasive among firms but not recognized well by business managers (Kahneman et al. 2016).

and other productivity related surveys such as the Annual Business Survey (ABS)), we show that management capabilities matter a lot for firms' forecasting and business performance.

The MES is the largest ever survey on management capabilities in the UK covering both manufacturing and non-manufacturing firms, with its survey design adapted from the established format of the World Management Survey (WMS).[25] Moreover, the MES collects expectations data at the business level, building on the US Management and Organizational Practices Survey (MOPS) and the Atlanta Fed Survey of Business Uncertainty (SBU).[26] The MES survey attempts to measure three aspects of firms' management practices: (1) *monitoring* – how well does the firm monitor its operations and use this information for continuous improvement (e.g. effectively collecting and using key performance indicators)? (2) *targets* – are the firm's targets stretching, tracked and appropriately reviewed? (3) *incentives* – is the firm promoting and rewarding employees based on performance, managing employee under-performance, making careful hiring decisions and providing adequate training opportunities? Based on the response to each question, we retrieve the management score for each firm using an identical methodology to the US MOPS, which facilitates international comparisons.

The MES survey reference year was 2016, but also collected firm-level expectations of turnover, expenditure, investment and employment growth for 2017 and 2018. In particular, the survey asked respondents to report their 2018 expectations using a 5-point bin, assigning a probability to each bin, for each of the four firm-level indicators. It also asks businesses to predict economy wide GDP growth 2017–18 using similar bins to the Bank of England's survey of external forecasters. This allows us to evaluate business forecasts against professional forecasters.

By combining a quantitative measure of management with direct expectations data of firms about both macro- and micro-outcomes, we obtain a set of robust stylized facts: Management practices vary substantially across firms – the 10th percentile of firms lacks robust monitoring or feedback processes, has limited performance incentives or employee training, while the 90th percentile are as well managed as leading firms internationally.

1. Management practices are strongly associated with superior firm performance – better managed firms have higher productivity, higher profitability, size, and a greater likelihood of exporting.

2. Management scores are higher in foreign-owned multinational firms and are lower in family-owned and family-run firms.

[25] See Scur et al (2021) on the WMS and also https://worldmanagementsurvey.org/

[26] See Buffington et al. (2017) on the US MOPS and Altig et al. (2020) on the SBU.

3. Better managed firms are able to make much more accurate forecasts about macro GDP growth and their own micro sales growth.

4. Firms with high management scores are also aware their micro and macro forecasts are more accurate in that they have lower subjective uncertainty in their predictions.

This suggests one driver of the superior performance of well managed firms could be they are better at forecasting, and being aware of this enables them to make better business decisions and rapidly optimize operational and strategic actions.

3.1.1 Related literature

This study shows that management matters for forecast quality at the firm level, highlighting the importance of firm expectations data combined with data on management practices. While large-scale data on firm expectations have been virtually non-existent until recently, there are increasingly more projects that break with this tradition by collecting direct expectations data to study firm performance as in Bloom et al. (2020) and Altig et al. (2020).[27] Our study is unique in that we combine direct expectations with large-scale data on management practices so that (1) quantitative management scores are available for each firm, (2) our sample includes many small and large firms, and (3) both GDP and firm level turnover growth forecasts are available. By combining forecasting data with management practice data we provide new evidence that pinpoints the role of management practices in driving forecast accuracy and firm performance. Furthermore, taking advantage of firm forecasts for a common macroeconomic object helps control for idiosyncratic components that may contaminate microeconomic forecasts of firm-specific growth (Tanaka et al. 2020).[28]

Our study also builds on recent papers that measure firm expectations directly.[29] We closely follow Bloom et al. (2020) and Altig et al. (2020) by asking firms to provide five-point subjective probability distributions of forecasts. Similar efforts, albeit with less detailed information being asked in their surveys, to collect data on subjective distributions of firm forecasts include Bachmann et al. (2018), Guiso and Parigi (1999), Bontempi et al. (2010), and Morikawa (2016).

[27] The seminal works by Coibion and Gorodnichenko (2012), Coibion and Gorodnichenko (2015), and Coibion et al. (2018) conducted a diagnostic study on how agents form expectations and how they respond to shocks.

[28] They show that forecast accuracy is positively correlated with profitability of firms using data on large firms GDP forecasts. Smaller forecast errors about turnover, for instance, may reflect that managers are better at forecasting their own outcomes but it could also be the case that it is just easier to predict turnover because they are stable, reflecting idiosyncratic business conditions rather than differences in manager's forecasting accuracy.

[29] Other papers that study micro-level expectations include Gennaioli et al. (2016) Bachmann and Elstner (2015), Bachmann et al. (2017), Coibion et al. (2020), and Boneva et al. (2020), among others.

Our study relies on large-scale data on management practices, which is scant in the empirical literature on management and firm performance (see, Bloom et al. 2011 for additional references). Our methodology is adapted from US MOPS to structure the survey and obtain quantitative scores of management practices; though, ours is the largest survey on management capabilities in the UK and, unlike the US MOPS, covers both manufacturing and non-manufacturing sectors.

In the following sections, we describe the survey design and the sampling process (Section 2), followed by in-depth description of our analysis on the variation in management practices across firms and the characteristics that appear to "drive" them (Section 3). We then discuss the relationship between firm performance and management (Section 4). Section 5 focuses on the relationship between management practices and firm forecasts. We conclude in Section 6.

3.2 Survey Design and Sample

3.2.1 Survey Questions

The MES was conducted by the ONS, in partnership with the Economic Statistics Centre of Excellence (ESCoE). It was sent to 25,006 firms and covered both the production and services industries. It was a voluntary survey of firms with ten or more employees, with the same frame as the Annual Business Survey (ABS) for 2016, allowing us to match to data on value added, employment, output and investment.[30] The sample was drawn through random sampling, stratified by employment size groups, industries and regions. It was stratified by (1) three employment size groups (10 to 49, 50 to 249 and 250 or more), (2) industries in sections B to S, (3) regions, including the nine NUTS1 English regions, Wales and Scotland.[31]

In the MES survey, there are 36 multiple choice questions drawn mostly from the 2015 US MOPS (Buffington et al. 2017). Sections B–D (12 questions) ask management practices. Section E (4 questions) asks decentralization practices. Section F (4 questions) asks business characteristics. Section G (10 questions) asks firm-level forecasts about micro-level outcomes (turnover, intermediate consumption, capital expenditure, and hiring) as well as

[30]Employment is defined as the total number of employees registered on the payroll and working proprietors. Further details on the Annual Business Survey (ABS) can be found in the ABS Quality and Methodology Information report and the ABS Technical Report.

[31]Sections included in the sample are, B: Mining and quarrying; C: Manufacturing, D: Electricity, gas, steam and air conditioning supply; E: Water supply; sewerage, waste management and remediation activities; F: Construction; G: Wholesale and retail trade; repair of motor vehicles and motorcycles; H: Transportation and storage; I: Accommodation and food service activities; J: Information and communication; L: Real estate activities; M: Professional, scientific and technical activities; N: Administrative and support service activities; P: Education; Q: Human health and social work activities; R: Arts, entertainment and recreation; S: Other service activities.

GDP. Section H (6 questions) asks feedback about the survey.

Focusing on the management questions (sections B–D), these ask about practices around monitoring, targets, incentives. For example, Section B asks how many key performance indicators are used and how frequently employees are evaluated against key performance indicators. Section C asks whether targets are set, and if so, how easy or difficult it is to achieve targets and it also asks who is aware of targets. Section D is about incentives asking how much each employee's performance and ability are reflected in performance bonuses or promotion. Each question is accompanied by a list of options from which respondents chose options closest to the practices within their firms. For each question, scores were awarded to each option on a scale of 0 to 1, where 0 was the least and 1 the most structured management practice. An overall management score was derived as a simple average of a firm's score on all individual questions (so a firm scoring 1 overall had the most structured response to all 12 questions).

Section G of MES focuses on expectations. It asks each firm to forecast the growth rate of real GDP in 2018, with the question reproduced in Figure 3.1. The questionnaire has seven growth bins which were taken from a Bank of England survey question sent to professional forecasters so we could evaluate firms' forecasts to professionals. We obtain expected GDP growth in 2018 as a weighted average of the seven bins taking their mid-points and twice the mid-point distance out for the end bins.[32]

We also asked firms to make forecasts about themselves (Figure 3.2). It asks a point forecast of 2017 total turnover, input costs, investment and hiring. It also asks firms to provide five-point subjective probability distributions of forecasts about the 2018 values of the same variables. Firms are given a blank "five-bin" scale and asked to fill five scenarios about their own future outcomes alongside probabilities. Granting them this degree of freedom is important because firm-level outcomes are widely dispersed across firms; pre-fixed bins are ill-suited for this situation because the range of outcomes requires a large number of bins, or very coarsely defined bins. From the subjective probability distributions, we retrieve both a firm's mean expectations for 2017 and 2018, and for 2018 a measure of subjective uncertainty. Comparing their expectations and realized outcomes we also obtain forecast errors for 2017 and 2018 (the difference between the firms' expectations and their eventual realized outcomes). The MES was dispatched in July 2017, about one year after the referendum in June 2016 on whether to leave the EU. There was considerable uncertainty about whether Brexit would actually occur, and if so when and what form it would take. After several rounds of negotiations with the EU side, Brexit was delayed. These facts

[32] The bins (points used for expectations) are: -4% or less (-5%), -3% to -2% (-2.5%), -1% (-1%), 0% (0%), 1% (1%), 2% to 3% (2.5%) and 4% or more (5%).

resulted in high-level uncertainty and made it difficult for UK firms to make accurate forecasts about future economic conditions both in macro and micro levels.

3.3 Descriptive Statistics

The MES survey was a voluntary survey on a sample of 25,006 firms and the total response rate was 38.7%. 56.5% did not respond and 4.8% elected to opt out of the voluntary survey.[33] For our analysis, we impose more restrictions so that firms in the sample have no more than two question non-responses out of the 12 management practice questions. We further ensure that firms in the sample have positive employment, leaving us with an analysis sample of 7,756 firms with management scores.

A set of descriptive statistics are in Table 3.1. Some firms have missing values for a few control variables (e.g. share of non-managers with a college degree).[34] Panel A of Table 3.1 focuses on the sample we use for examining the drivers of management and its association with performance. The performance measures such as employment and productivity (value added per worker) are taken from the 2016 ABS. Firm employment size is 69 at the median and 283 at the mean. The average firm age is 17 years old, about 40% (24%) of managers (non-managers) have degrees, 42% of firms are family owned and run, 13% are foreign owned and 36% export. Firms have an average management score of 0.59 with a standard deviation of 0.2.

Panel B of Table 3.1 looks at the expectations sample separating these into macro forecasts (the first three rows), micro forecasts and uncertainty measures. Firms were pessimistic about macro growth 2017–18, with an average prediction of 0.1%, even though the out-turn was 1.4%. The forecast error is the (absolute) difference between the firm's estimates and the actual out-turn which unsurprisingly gives a mean and median error of about 1.4%.

We can also compare firm estimates to those of professional forecasters in the Bank of England's Survey. Figure 3.3 gives the distributions showing that businesses were somewhat more pessimistic than professional forecasters.[35] Firm forecasts on GDP are skewed left in that firms assign a higher percentage of likelihood that real GDP growth is -1% or less (bin 1) and -1% to 1% (bin 2), relative to the average forecasts among professional forecasters. On the other hand, firms assign a lower percentage of likelihood that real GDP growth is

[33] See, for more information on the response rates and firm characteristics, the ONS website.

[34] To keep the sample size stable across columns of the regression tables, for each question we generate a dummy variable equal to one for missing values (and zero otherwise), set the missing values equal to the mean and add the vector of these missing dummies to the regressions. Results are essentially unchanged if we condition on the sample of firms with all non-missing variables.

[35] To facilitate comparison, we convert the original seven bins into four bins: (1) -1% or less, (2) -1% to 1%, (3) 1% to 3%, (4) 3% or more.

1% to 3% (bin 3) and 3% or more (bin 4) than the average forecasts among professional forecasters. Our "disagreement" measure is the absolute value of difference between each firm's forecast for GDP growth and the average forecasts in the Bank of England's survey of external forecasters. Unsurprisingly (since the mean of forecasters was close to the actual out-turn), the disagreement variable mean is quite similar to the forecast error (1.3%).

The next block of descriptives in Table 3.1 Panel B are forecasts of firm level outcomes. For the 2016–17 period, the median firm was reasonable accurate with a forecast turnover growth of 4.6% compared to an outcome of 4.7%. The large standard deviation indicates a wide degree of variation, however. If we instead look at the absolute forecast error, the median is 6%. This suggests the substantial difficulties many firms face in accurately assessing their end year growth, even in the middle of the year (when half the data has been realized). We then construct the same statistics for the 2016–18 forecasts. As one might expect, firms found even more difficulty in forecasting this far out; the median forecast was for 4.6% growth over the whole period compared to an actual out-turn of 9%, suggesting the same pessimism as the macro forecast. It is worth noting the survey was conducted in the year after the Brexit vote which generated substantial policy uncertainty. Again, the absolute forecast error is large with a median of 11%.

Comparing the macro and micro forecasts, it appears to be more difficult to forecast their own turnover than GDP. For instance, the median of GDP forecast errors is 1.4%, whereas it is 11% for firm turnover forecasts. The final block of descriptives in Panel B is on forecast uncertainty. We measure this as:

$$Uncertainty_i = \sqrt{\sum_i \left(Growth_{ij} - \overline{Growth_i}\right)^2 \cdot Likelihood_{ij}}$$

where $Growth_{ij}$ is the firm i's forecast in bin j, $\overline{Growth_i}$ is the sample average of the firm i's forecasts over these bins, and $Likelihood_{ij}$ is the likelihood that firm i attached to bin j.

It is clear that the forecast distribution is more dispersed about turnover than about GDP: 0.4% vs. 1.7% at the mean. This is broadly consistent with those of Bloom et al. (2019), who estimate the size of uncertainty for both aggregate and idiosyncratic TFP and show micro-uncertainty is about five times larger than macro-uncertainty. Moreover, we show that micro-uncertainty is larger than macro-uncertainty and robust to the choice of measures in that either we use forecast errors (ex-post measure of uncertainty) or dispersion of forecasts (ex-ante measure of uncertainty).

Figure 3.4 presents three binscatters with some basic sense checks of the data. Panel A shows that firms with higher GDP forecast uncertainty have greater GDP forecasting errors on average. Panel B shows a similar relationship for turnover, with firms with higher turnover uncertainty providing forecasts with greater average absolute error. Panel C shows that firms' GDP and turnover uncertainty are positively correlated, so the factors that lead to better or worse macro and micro forecasting confidence are common across firms. In what follows, we will analyze the factors that might explain the accuracy and confidence with which firms are making their macro and micro-economic forecasts. A common theme emerges that firms with more structured management practices make more certain and more accurate forecasts and as a consequence, better business decisions.

3.4 Drivers of Management Practices

Management practice differs significantly across and within countries (Bloom and Van Reenen 2007). We first look at the cross-sectional dispersion of management scores, then examine how firm-level characteristics are related to management practices. Figure 3.5 displays the kernel density plot of the management scores within three broad size classes of firms (10–49; 50–249 and 250 plus employees). There is wide variation in all three groups, consistent with evidence from other studies. The mean and median of the distribution increases with firm size, suggesting that larger firms have higher scores. There is also a hint of larger dispersion amongst smaller firms. Table 3.2 investigates this relationship across six broad industries using four size bins. The final row reproduces the result that mean management scores rises monotonically as firm size bins get larger, and this is generally true across all sectors. There is some variation in mean management scores across sectors with the construction industry particularly low (0.43) and business services particularly high (0.53).

Table 3.3 reports how management scores are correlated with various characteristics. Measuring firm size by log employment, column (1) corroborates the statistical significance of Figure 3.5 and Table 3.2. Column (2) then includes fixed effects for two-digit industry and location (11 regions) and "Other Controls" (dummies for the month when the survey was returned; time spent on the survey; reporting accuracy indicator[36] and a multi-site dummy). The size of coefficient hardly changes (from 0.063 to 0.061) and remains highly significant. Column (3) includes ownership/governance dummies. Foreign-owned firms have significantly higher management scores and family-run firms have significantly lower scores. Family-owned firms who are run by professional outside managers are no worse than other firms.

To dig deeper into the family firm effects, columns (5) through (7) of Table 3.3 re-run the specification of column (4), but split the sample by the size bands of Figure 3.5.

[36]This is measured by the disparity between turnover reported in ABS 2016 and as declared in the MES 2016.

The coefficient on family owned and run is monotonically decreasing with firm size. It suggests that being family-run is not a disadvantage for smaller firms; being family run presents a severe management disadvantage for larger firms. By contrast, foreign ownership is positively associated with better management throughout the size distribution, with its effect particularly large for smaller firms. Turning to the other variables, the skills of both managers and non-managers are significantly positively correlated with higher management scores across all columns. Older firms have significantly lower management scores, but only in the smallest size category. This suggests that although there may be a cohort effect, with more recent firms adopting modern management practices, competitive selection effects offset this for firms with over 50 employees.[37]

3.5 Management and Firm Performance

It is well understood that productivity varies substantially across firms and establishments (e.g., Syverson 2011). We now study the relationship between firm performance indicators and management practices. Columns (1) through (7) of Table 3.4 use labor productivity (log gross value added per worker) as the dependent variable. Column (1) is a simple bivariate regression and shows a strong and significant positive relationship between productivity and management score. This implies that a one standard deviation increases in the management score (0.196) is associated with a 0.166 log point increase in productivity.[38] Column (2) adds in the industry, location and other basic controls from Table 3.3. Columns (3) and (4) then include the log capital-labor ratio[39], log employment and other controls (age, skills, ownership). Even with all these variables included simultaneously in column (4) the coefficient on management is still large at 0.724 and statistically significant. Looking at the coefficients on the other variables, the output elasticity with respect to capital is low at 0.13 and we obtain somewhat decreasing returns to scale as indicated by the negative coefficient on labour inputs. As with management, family firms have lower productivity and multinationals higher productivity. Older firms appear more productive, consistent with selection effects: older firms are those who have managed to survive competitive market pressures.

[37] It is only among the smaller firms who are able to "hang on" (possibly because they operate in product niches, somewhat shielded from competition), that the cohort effect dominates the selection effect.

[38] Alternatively, increasing the management score from the 10th to the 90th percentile (0.509 as show in base of Table 3.4) is associated with a 0.43 log point increase in productivity.

[39] For our capital stock series, we apply the perpetual inventory method, starting from the firm's initial level of capital stock to generate a subsequent series of capital stock using the firm-level investment data from the ABS (2008–2016) and industry-level deflators. We use a capital depreciation rate of 12%. Initial capital stock is calculated by assuming that the firm is in steady state, so the initial investment rate is divided by the depreciation rate plus the steady state growth rate (assumed to be a three year moving average of the GDP growth rate).

Columns (5) through (7) of Table 3.4 split by employment size. Management scores have positive and significant coefficients across all size bands, and the magnitude is not significantly different for large firms than smaller ones. We switch the dependent variable to profit per employee in column (8) and an exporting dummy in column (9).[40] The management score has a positive and significant coefficient on both of these alternative measures of success.

3.6 Forecast Accuracy, Uncertainty and Management

We turn to examine the relationship between management practices and forecast accuracy. In this section, we restrict our sample to satisfy three criteria for "good responses". Firstly, firms must complete at least two bins (see Figures 3.1 and 3.2) with full information. Secondly, the values answered for five scenarios about their own future outcomes must be weakly increasing from the lowest to the highest bin. Finally, the sum of percentage likelihoods in these bins must be within range of 90% to 110%. The share of the firms in our sample which satisfy these criteria is 88% and is comparable to that in the US MOPS (85% in Bloom et al. 2020).[41]

3.6.1 Forecasting *macro-level* outcomes: GDP forecasts by well-managed firms are more accurate

Figure 3.6 shows the relationship between GDP forecast errors and three firm characteristics – management, productivity and profitability. The horizontal axis in each panel has absolute GDP forecast error grouped into 40 equal-sized bins. The vertical axis of Panel A shows the mean values of management scores in each bin. There is a clear negative relationship indicating that better managed firms make lower GDP forecast errors. Panel B uses productivity instead of management and Panel C uses profitability, which also show negative gradients (consistent with Tanaka et al. 2020), although the relationship is noisier.[42]

We address this issue in Table 3.5, where we go beyond these bivariate correlations and control for many other factors. Column (1) reports the result of regressing a measure of forecast errors on the management score, confirming the statistical significance of the

[40] We define profit as gross value added minus labor costs. Exporting is a dummy indicating if a firm exports any goods or services outside the UK, and zero otherwise.

[41] Firms that can return good responses have certain characteristics. In Table 3.A1, we regress good response dummies on various firm characteristics. In general, good responses are from firms with good management practice and a large fraction of managers with a college degree. These findings are also consistent with those in the US MOPS.

[42] We also show in the Appendix Tables 3.A2, and that firms with higher manager scores are more optimistic about GDP and turnover future growth, respectively. This is consistent with their higher accuracy as firms on average were 1.4% too pessimistic.

relationship in Panel A of Figure 3.6. Column (2) adds in industry dummies, location dummies and the standard other controls. Firms with more structured management practice still make significantly smaller forecast errors. In column (1), the coefficient of -0.358 implies that an increase in management scores from the 10th to 90th percentile (0.509) is associated with a fall in the absolute value GDP growth forecast errors of 0.18 percentage points, or 13% of the mean of the dependent variable (1.411 as shown in the base of the column). Columns (3) to (5) show the conditional correlations of GDP forecast error with firm size, foreign ownership and family firms and column (6) presents the full regression of management with all these variables as well as age and skills. Although the management coefficient falls to -0.171, it remains significant. The only other significant variable in the saturated model is employment: larger firms make significantly better GDP forecasts.

As a robustness test, we compare GDP forecasts of firms to those of professional forecasters in the Bank of England's survey of external forecasters as another way to evaluate the reasonableness of firms' forecasts. We show the results of a regression of $Disagreement_i$ (between the firm and the mean of professional forecasters) on firm characteristics in column (7) of Table 3.5. The coefficient on management score is negative and significant, and similar in magnitude to column (6), indicating that forecasts of better-managed firms align better with those of external forecasters. This may indicate that large firms with structured management practices either have similar information and analytical ability to external forecasters, or that they simply pay more attention to reports in the public domain of such forecasts.

3.6.2 Forecasting *micro-level* outcomes: turnover forecasts by well-managed firms are more accurate

We now turn to explore the relationship between firms' forecasts about their own growth and their characteristics. Our measure of forecast errors is the absolute value of the difference between expected and actual turnover growth rate. In the survey, we asked turnover forecasts for two different horizons: one for 2017 and one for 2018. We thus obtained forecast errors for 2017 and 2018, respectively. Taking the average of two forecast errors, we use it as a measure of forecast accuracy and study its relationship with management capabilities.[43] Note that the number of observations analyzed in this section is smaller compared to those in the previous sections because we need to observe the same firm over two years to obtain realizations and calculate the actual growth rate of turnover.[44]

[43] Technically, we inverse weight the regressions by number of usable responses per firm, so that each firm only count for one observation even though it may have an outturn in 2017 and 2018.

[44] We exclude firms reporting zero turnover in both MES and ABS from the analysis.

Figure 3.7 illustrates the relationship between forecast accuracy with the same firm characteristics of Figure 3.6. As with GDP forecast errors, better managed firms (as well as those with higher productivity and profits) make significantly more accurate forecasts about their own sales. There appears to be more outliers, however, with some very large errors of 100% or more (even after winsorizing at the top and bottom percentiles). To investigate whether the relationship is driven by outliers, Figure 3.A1 shows what happens if we drop all observations with a forecast error of 50% or greater (Panel A) or 25% or greater (panel B). The negative relationship between management and forecast error still seems to hold up even when we drop large parts of the sample.

Table 3.6 uses forecast accuracy about firm-level turnover as the dependent variable. Turnover forecast errors are significantly smaller for better-managed firms as shown in column (1). The coefficient of -6.108 implies that shifting management scores from the 10th to 90th percentile (0.509) is associated with a fall in the absolute value of the forecast error of 3.11 percentage points. This is 20% of the mean of the dependent variable – a substantial effect. The magnitude of the management coefficient remains large at -4.236 in column (2) after including for industry, location and standard controls. Column (3) shows that the firm's turnover volatility[45] in the past five years is associated with a greater forecasting error as one might expect. Column (4) shows that larger firms also make less forecasting errors. Column (5) presents the saturated model with all these controls as well as the others from Table 3.5.[46] The management coefficient remains negative, significant and large at -5.068.[47]

3.6.3 Comparing forecasts about GDP and turnover: well-managed businesses manage uncertainty better

As noted in Section 2, we construct a measure of uncertainty over the firm's macro and micro forecast. Column (1) of Table 3.7 reports how subjective uncertainty is significantly and negatively correlated with management. An increase in the score from the 10th to 90th percentile is associated with a 0.43 log point decrease in uncertainty (25% of the mean of the dependent variable). This relationship remains significant when the usual control variables are added in columns (2) and (3), although the coefficient drops from -0.845 to -

[45] Volatility is measured as the five year standard deviation of the firm's annual change in log(turnover).

[46] The only real surprise in this column is that the family run firm variable has a negative and significant coefficient. They seem to make more accurate forecasts about their own future even though their make poorer forecasts about the macro economy. This might be because they operate in much more stable and less risky environments – and take less chances themselves (see Sraer and Thesmar 2007).

[47] In both Tables 3.5 and 3.6, the management score remains significant even after controlling for productivity and profitability from Figures 3.6 and 3.7. The results are also robust to trimming on outliers as in Figure 3.A1.

0.196.[48] Columns (4) through (8) use subjective uncertainty on other dimensions, specifically employment, intermediate consumption, capital expenditure and GDP. These show that better managed firms have lower subjective uncertainty.

The weakest statistical uncertainty-management relationship is with GDP uncertainty. While management scores are negatively and significantly correlated with GDP uncertainty in column (7) the management coefficient is insignificant in the saturated model of column (8). It is tempting to conclude that well-managed firms are better at forecasting their own outcomes (which are presumably most relevant for their performance) than GDP. However, the magnitudes are not so different. Using our usual experiment of increasing management by 0.509 implies that turnover uncertainty is reduced by 6.2% of the mean in column (3) compared to 4.9% of the mean in the equivalent GDP uncertainty of column (8). Hence, the economic significance is similar.[49]

3.7 Conclusions

This study reports results from the MES, the largest management survey in the UK linked to firm panel data on productivity. We document that: (i) there is a large variation in UK management practices; (ii) productivity, profitability and size are significantly higher in firms with more structured management, and (iii) that structured management is systematically greater in firms that are foreign owned and more skilled, and lower in firms that are family owned or run.

In terms of expectations, we compare firm's forecasts of one year ahead growth to actual outcomes observed in the years following the survey. We are able to show that firms with higher management scores are significantly more accurate in their forecasts about macroeconomic growth (GDP) and their own growth (turnover). This statement is true even after controlling for many factors correlated with management. Large and more productive firms are also better at forecasting, for example, and these features are correlated with management. However, even after conditioning on these firm characteristics (as well as ownership, age, industry and location), well managed firms are significantly better forecasters. Moreover, they are more confident forecasters having less subjective uncertainty over their forecasts than other firms.

If better management enables superior predictions of growth, then firms are more likely to be making optimal decisions over the appropriate composition of factor inputs (as well as other more strategic decisions). To put it simply, better managed firms make better forecasts

[48] As in Table 3.6, we exclude firms reporting zero turnover in both MES and ABS from the analysis.

[49] The shrinkage of the management coefficients between columns (2) and (3) is similar to that between columns (7) and (8).

and as a consequence better business decisions. The higher productivity and profitability of well managed firms may rest, at least in part, over this better allocation of factors, a micro-level equivalent of the macro-level findings in Hsieh and Klenow (2009). This is a hypothesis we intend to pursue in future work.

3.8 Reference

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Table 3.1. Descriptive Statistics

Variables	# of obs	Mean	Median	SD
Panel A: Management				
Management score	7756	0.586	0.627	0.196
Employment at 2016 IDBR	7756	282.606	69	1070.225
Firm age	7756	16.695	21	7.418
Log GVA per worker	7346	3.648	3.707	1.059
Share of managers with a college degree	7496	0.397	0.350	0.347
Share of non-managers with a college degree	7109	0.236	0.100	0.269
Family owned but not run	7717	0.112	0	0.315
Family owned and run	7717	0.425	0	0.494
Foreign owned	7756	0.132	0	0.338
Profit per worker	7756	26.756	10.295	63.900
Exporting likelihood	7756	0.355	0.000	0.479
Panel B: Expectations (shown as percentage)				
Macro forecasts				
Expected GDP growth 2017–18	7756	0.096	0.000	1.047
Absolute GDP forecast error 2018	7756	1.410	1.398	0.918
Absolute GDP disagreement	7756	1.301	1.263	0.900
Micro forecasts				
Turnover growth forecast 2016–17	7563	5.236	4.597	17.343
Realized turnover growth 2016–17	4959	5.443	4.710	34.072
Turnover forecast errors 2016–17	4853	0.174	-0.029	27.499
Turnover growth forecast 2016–18	7621	-7.573	4.580	57.861
Realized turnover growth 2016–18	3398	10.366	9.014	40.180
Turnover forecast errors 2016–18	3353	-14.266	-2.916	59.454
Absolute turnover forecast errors 2016–17	4853	14.229	5.965	27.611
Absolute turnover forecast errors 2016–18	3353	31.044	11.395	54.020
Average absolute turnover forecast error (2017 and 2018 pooled)	5140	21.164	8.596	35.902
Uncertainty				
GDP uncertainty 2018	6705	0.439	0.541	0.425
Turnover uncertainty	6923	1.698	1.757	0.864

Note: These are descriptives from the data (MES and ABS). Details in text. Panel A is the cleaned sample for management analysis. Profit per worker is winsorized at top and bottom 1%. Panel B focuses on subsample which has expectations information. To construct micro forecast errors we need realized outcomes from the ABS which is why the sample size is smaller. All variables in Panel B are winsorized at the top and bottom 1% of the distribution. Uncertainty measures are in logarithm.

Table 3.2. Management Scores by Broad Industry

	Employment 10–49		Employment 50–99		Employment 100–249		Employment 250+		All	
	Mean	Share	Mean	Share	Mean	Share	Mean	Share	Mean	Share
Manufacturing	0.47	7.10	0.58	3.75	0.64	3.08	0.71	4.09	0.58	18.02
Construction	0.43	5.89	0.56	1.71	0.63	0.99	0.67	1.16	0.50	9.76
Retail, distribution, hotels and restaurants	0.49	9.45	0.62	3.30	0.64	2.40	0.73	5.83	0.60	20.98
Transport, storage and communication	0.52	3.38	0.57	1.47	0.64	1.16	0.72	2.09	0.60	8.10
Business services	0.53	6.58	0.63	2.58	0.62	2.99	0.68	5.27	0.61	17.42
Real estate and others	0.49	8.34	0.59	4.05	0.62	3.73	0.68	9.61	0.60	25.72
Total	0.49	40.70	0.60	16.84	0.63	14.33	0.69	28.13	0.59	100

Note: Mean shows the average management score for the firms in the industry and employment size categories. Share describes the share of firms in the industry and employment size categories out of the full sample.

Table 3.3. "Drivers" of Management Scores

Dependent Variable:				**Management Score**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample:	All	All	All	All	Employment 10–49	Employment 50–240	Employment 250+
Log employment	0.063***	0.061***	0.055***	0.057***	0.108***	0.043***	0.022***
	(0.0014)	(0.0017)	(0.0018)	(0.0018)	(0.0079)	(0.0071)	(0.0039)
Family owned but not run			-0.009	-0.004	-0.012	-0.001	-0.007
			(0.0065)	(0.0065)	(0.0129)	(0.0107)	(0.0094)
Family owned and run			-0.025***	-0.015***	0.007	-0.020**	-0.042***
			(0.0050)	(0.0050)	(0.0089)	(0.0083)	(0.0087)
Foreign owned			0.053***	0.046***	0.093***	0.046***	0.025***
			(0.0054)	(0.0054)	(0.0144)	(0.0093)	(0.0071)
Log age				-0.016***	-0.036***	-0.010	0.002
				(0.0031)	(0.0050)	(0.0065)	(0.0040)
Share of managers with				0.061***	0.063***	0.063***	0.028*
a college degree				(0.0079)	(0.0127)	(0.0137)	(0.0141)
Share of non-managers with				0.058***	0.071***	0.050***	0.031*
a college degree				(0.0103)	(0.0165)	(0.0181)	(0.0172)
Industry Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes
Location Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7756	7756	7756	7756	3160	2421	2175
R2	0.212	0.307	0.319	0.341	0.272	0.246	0.243

Note: Estimation by OLS with robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Management score is the unweighted average of the score for each of the 12 questions, with scores on a scale of 0 to 1 for each question, where 0 was the least and 1 the most structured management practice. Firm employment is from the ABS in 2016. "Foreign owned" is a dummy for whether the firm is an affiliate of a non-UK firm. "Family owned and run" is a firm owned by a family and run by a family member; "Family owned but not run" is a dummy for a firm which is family owned but whose CEO is a non-family member (a firm which is not owned by a family is the omitted base) from MES. Age is the dated from the date of incorporation from the ABS. Share of managers with a college degree and share of non-managers with a college degree is from MES. Industry dummies are two-digit, location dummies are the 9 NUTS1 regions and "Other Controls" includes dummies for the month when the survey was returned, time spent on the survey, multi-site dummy and reporting accuracy indicator (difference between 2016 employment as reported in ABS and MES).

Table 3.4. Firm Performance (Productivity, Profits and Exports) and Management Score

Dependent Variable:	Log (Gross Value Added per worker)							Profit Per Worker	Export
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sample:	All	All	All	All	Employment 10–49	Employment 50–240	Employment 250+	All	All
Management score	0.845***	0.846***	0.790***	0.724***	0.754***	0.670***	0.661***	18.878***	0.125***
	(0.0662)	(0.0640)	(0.0680)	(0.0693)	(0.1041)	(0.1227)	(0.1883)	(4.2240)	(0.0264)
Log employment			-0.102***	-0.101***	-0.062	-0.201***	-0.035	-5.271***	0.009**
			(0.0117)	(0.0117)	(0.0415)	(0.0449)	(0.0271)	(0.7429)	(0.0046)
Log capital per worker			0.131***	0.128***	0.130***	0.120***	0.165***	6.303***	0.021***
			(0.0076)	(0.0075)	(0.0125)	(0.0124)	(0.0173)	(0.5479)	(0.0026)
Log age			0.063***	0.064***	0.097***	0.078**	0.013	-0.963	0.030***
			(0.0193)	(0.0191)	(0.0309)	(0.0366)	(0.0332)	(1.1449)	(0.0065)
Family owned but not run			-0.076**	-0.066*	-0.079	0.004	-0.041	-2.202	-0.033**
			(0.0359)	(0.0357)	(0.0686)	(0.0582)	(0.0683)	(2.4556)	(0.0154)
Family owned and run			-0.119***	-0.102***	-0.065	-0.114***	-0.112**	-3.738**	-0.056***
			(0.0257)	(0.0255)	(0.0440)	(0.0436)	(0.0499)	(1.7122)	(0.0111)
Foreign owned			0.186***	0.171***	0.356***	0.226***	0.029	9.742***	0.113***
			(0.0354)	(0.0354)	(0.0959)	(0.0604)	(0.0529)	(2.9841)	(0.0163)
Share of managers with				0.082*	0.036	0.133*	0.128	0.029	0.058***
a college degree				(0.0425)	(0.0616)	(0.0776)	(0.0908)	(2.5105)	(0.0165)
Share of non-managers with				0.286***	0.343***	0.154	0.263**	6.516	0.092***
a college degree				(0.0630)	(0.0972)	(0.1141)	(0.1253)	(4.0643)	(0.0236)
Industry Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Difference in management scores between 10 and 90 percentiles	0.509	0.509	0.509	0.509	0.509	0.509	0.509	0.509	0.509
Observations	7346	7346	7346	7346	3023	2305	2018	7756	7756
R2	0.025	0.334	0.390	0.395	0.378	0.460	0.513	0.195	0.414

Note: Estimation by OLS with robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable is log gross value added per worker in columns (1) - (7); profits per worker, winsorized with top and bottom 1%, in column (8) and an exporting dummy in column (9). Employment and capital constructed from the ABS. "Foreign Owned" is a dummy for whether the firm is an affiliate of a non-UK firm. "Family owned and run" is a firm owned by a family and run by a family member; "Family owned but not run" is a dummy for a firm which is family owned but whose CEO is a non-family member (a firm which is not owned by a family is the omitted base). Age is the dated from the date of incorporation. Industry dummies are two-digit, location dummies are the 9 NUTS1 regions and "Other Controls" includes dummies for the month when the survey was returned, time spent on survey, a multi-site dummy and reporting accuracy indicator. See Table 3.1 notes and text for more details.

Table 3.5. GDP Forecast Errors and Management Score

Dependent Variable:	**Absolute GDP Forecast Error**						**GDP Disagreement**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Management score	-0.358***	-0.293***				-0.171**	-0.154**
	(0.0609)	(0.0673)				(0.0738)	(0.0725)
Log employment			-0.066***			-0.054***	-0.055***
			(0.0103)			(0.0115)	(0.0113)
Foreign owned				-0.040		0.035	0.036
				(0.0338)		(0.0365)	(0.0358)
Family owned but not run					0.066*	0.047	0.049
					(0.0391)	(0.0395)	(0.0388)
Family owned and run					0.073***	0.031	0.033
					(0.0269)	(0.0295)	(0.0289)
Log age						0.018	0.016
						(0.0175)	(0.0171)
Share of managers with						-0.030	-0.027
a college degree						(0.0474)	(0.0465)
Share of non-managers						0.087	0.088
with a college degree						(0.0641)	(0.0627)
Industry Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes
Location Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	1.411	1.411	1.411	1.411	1.411	1.411	1.304
Observations	7134	7134	7134	7134	7134	7134	7134
R2	0.005	0.055	0.058	0.053	0.054	0.060	0.061

Note: Estimation by OLS with robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable in columns (1) to (6), is the absolute value of the difference between expected (in MES 2016) and actual real GDP growth rate 2017–18. In column (7), the dependent variable is the measure of GDP disagreement between firms and Bank of England's external forecasters (see text). Employment and capital constructed from the ABS. "Foreign Owned" is a dummy for whether the firm is an affiliate of a non-UK firm. "Family owned and run" is a firm owned by a family and run by a family member; "Family owned but not run" is a dummy for a firm which is family owned but whose CEO is a non-family member (a firm which is not owned by a family is the omitted base). Age is the dated from the date of incorporation. Industry dummies are two-digit, location dummies are the 9 NUTS1 regions and "Other Controls" includes dummies for the month when the survey was returned, time spent on survey, a multi-site dummy and reporting accuracy indicator. See Table 1 notes and text for more details.

Table 3.6. Forecast Error in Firm's Estimate of its Future Turnover and Management Score

Dependent Variable:	**Absolute Forecast Error in Firm's Future Turnover**				
	(1)	(2)	(3)	(4)	(5)
Management score	-6.108***	-4.236*			-5.068**
	(1.9132)	(2.1735)			(2.3997)
Five-year turnover volatility			14.037***		13.876***
			(3.5425)		(3.5326)
Log employment				-0.670*	-0.037
				(0.3658)	(0.4654)
Foreign owned					0.825
					(0.9641)
Family owned but not run					-0.382
					(1.1090)
Family owned and run					-1.624**
					(0.8131)
Log age					-1.540**
					(0.6323)
Share of managers with					0.787
a college degree					(1.4730)
Share of non-managers with					3.959*
a college degree					(2.2128)
Industry Dummies	No	Yes	Yes	Yes	Yes
Location Dummies	No	Yes	Yes	Yes	Yes
Other Controls	No	Yes	Yes	Yes	Yes
Mean of dep. var.	15.213	15.213	15.213	15.213	15.213
Observations	4676	4676	4676	4676	4676
R2	0.002	0.150	0.160	0.150	0.167

Note: Estimation by OLS with robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is the average of the absolute value of the difference between actual and expected growth rates. We do this for 2016–2017 and also 2016–2018 (and re-weight the regression if the firm error is available in both years so that each firm is only counted once). We exclude firms reporting zero turnover in both MES and ABS from the analysis. Employment is from the ABS. "Foreign Owned" is a dummy for whether the firm is an affiliate of a non-UK firm. "Family owned and run" is a firm owned by a family and run by a family member; "Family owned but not run" is a dummy for a firm which is family owned but whose CEO is a non-family member (a firm which is not owned by a family is the omitted base). Age is the dated from the date of incorporation. Industry dummies are two-digit, location dummies are the 9 NUTS1 regions and "Other Controls" includes dummies for the month when the survey was returned, time spent on survey, a multi-site dummy and reporting accuracy indicator. See Table 1 notes and text for more details.

Table 3.7. Uncertainty Over Forecasts and Management Scores

Dependent Variable:	(1) Turnover Uncertainty	(2) Turnover Uncertainty	(3) Turnover Uncertainty	(4) Employment Uncertainty	(5) Intermediate Consumption Uncertainty	(6) Capital Expenditure Uncertainty	(7) GDP Uncertainty	(8) GDP Uncertainty
Management score	-0.845***	-0.541***	-0.196***	-0.287***	-0.152**	-0.194**	-0.169***	-0.042
	(0.0549)	(0.0570)	(0.0620)	(0.0603)	(0.0670)	(0.0857)	(0.0280)	(0.0341)
Log employment			-0.125***	-0.200***	-0.103***	-0.162***		-0.015***
			(0.0104)	(0.0103)	(0.0110)	(0.0138)		(0.0056)
Foreign owned			-0.028	-0.094***	-0.009	-0.162***		0.014
			(0.0335)	(0.0321)	(0.0355)	(0.0448)		(0.0178)
Family owned but not run			0.082**	0.097***	0.075**	0.071*		0.024
			(0.0330)	(0.0312)	(0.0361)	(0.0427)		(0.0184)
Family owned and run			0.141***	0.095***	0.153***	0.060*		0.061***
			(0.0240)	(0.0233)	(0.0259)	(0.0327)		(0.0133)
Log age			-0.096***	-0.125***	-0.097***	-0.052**		-0.026***
			(0.0149)	(0.0147)	(0.0164)	(0.0208)		(0.0081)
Share of managers with			-0.009	-0.031	0.030	-0.037		0.000
a college degree			(0.0395)	(0.0370)	(0.0427)	(0.0518)		(0.0213)
Share of non-managers with			0.058	-0.029	0.080	-0.173**		-0.013
a college degree			(0.0549)	(0.0487)	(0.0586)	(0.0701)		(0.0289)
Industry Dummies	No	Yes	Yes	Yes	Yes	Yes	No	Yes
Location Dummies	No	Yes	Yes	Yes	Yes	Yes	No	Yes
Other Controls	No	Yes	Yes	Yes	Yes	Yes	No	Yes
Mean of dep. var.	1.695	1.695	1.695	1.619	1.591	2.828	0.439	0.439
Observations	6833	6833	6833	6628	6816	5890	6705	6705
R2	0.035	0.194	0.232	0.278	0.186	0.151	0.006	0.062

Note: Estimation by OLS with robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is the log subjective uncertainty regarding the forecast over turnover in columns (1)–(3), over employment, intermediates and capital expenditure in the next three columns and over GDP in the final column (see text for details). For turnover uncertainty, we exclude firms reporting zero turnover in both MES and ABS from the analysis. Employment is from the ABS. "Foreign Owned" is a dummy for whether the firm is an affiliate of a non-UK firm. "Family owned and run" is a firm owned by a family and run by a family member; "Family owned but not run" is a dummy for a firm which is family owned but whose CEO is a non-family member (a firm which is not owned by a family is the omitted base). Age is the dated from the date of incorporation. Industry dummies are two-digit, location dummies are the 9 NUTS1 regions and "Other Controls" includes dummies for the month when the survey was returned, time spent on survey, a multi-site dummy and reporting accuracy indicator. See Table 1 notes and text for more details.

Figure 3.1. MES Questionnaire on Macro Growth Expectations

30. Please indicate what likelihood you would attach to the possible 2018 rates of UK economic growth (real growth rate of Gross Domestic Product) below.
Gross Domestic Product (GDP) is the main measure of the size of the UK economy, based on the value of goods and services produced during a given period.

UK Economic Growth in 2018		Percentage likelihood (values in this column should sum to 100)	
Strong decline	-4% or less	2 %	1138
Moderate decline	-2% to -3%	5 %	1139
Slight decline	-1%	10 %	1140
No change	0%	30 %	1141
Slight increase	1%	40 %	1142
Moderate increase	2% to 3%	10 %	1143
Strong increase	4% or more	3 %	1144
	Total	100 %	

Note: This is the macro growth expectations question from the MES.

Figure 3.2. MES Questionnaire on Micro Growth Expectations

The example below will help you to complete questions 22, 24, and 26

Example A:
Jane Smith is filling out this survey for Business A. In 2016, Business A had approximately £4,500,000 in turnover, with a forecast of £4,750,000 in 2017.

For calendar years 2016 and 2017, what are the approximate values of turnover, including exports and other receipts within this business? If applicable exclude freight charges, excise taxes and value added tax.

For 2016 calendar year.. £ 4,500,000

Forecast for 2017 calendar year.. £ 4,750,000

The example below will help you to complete questions 23, 25, 27 and 29

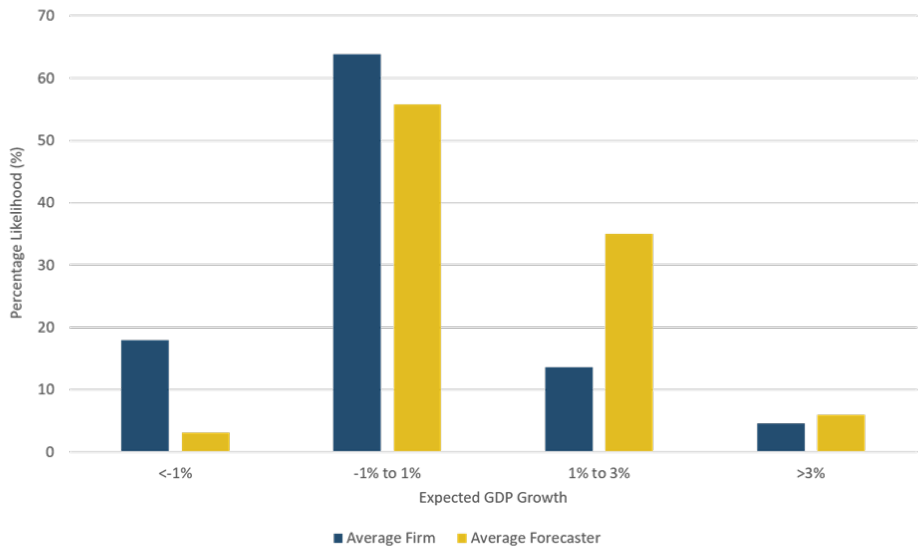
Example B:
Jane also knows that turnover at Business A is forecast to grow approximately an additional 5% in 2018, with predicted annual value of turnover of £5 million. However, Jane knows there is some uncertainty with that forecast and that the value of turnover next year could be more or less than £5 million depending on consumer demand, changes in prices, and other uncertainties in the market. Given this uncertainty, Jane estimates that turnover will be between £2.8 million and £7.5 million, and thinks the likelihood of each scenario is as shown in the table below.

Looking ahead to the 2018 calendar year, what is the approximate value of turnover you would anticipate for this business in the following scenarios, and what likelihood do you assign to each scenario?

2018 scenarios, from lowest to highest	Approximate turnover in 2018	Percentage likelihood (values in this column should sum to 100)
LOWEST	£ 2,800,000	5 %
LOW	£ 4,200,000	10 %
MEDIUM	£ 5,000,000	60 %
HIGH	£ 6,300,000	20 %
HIGHEST	£ 7,500,000	5 %
	Total	100 %

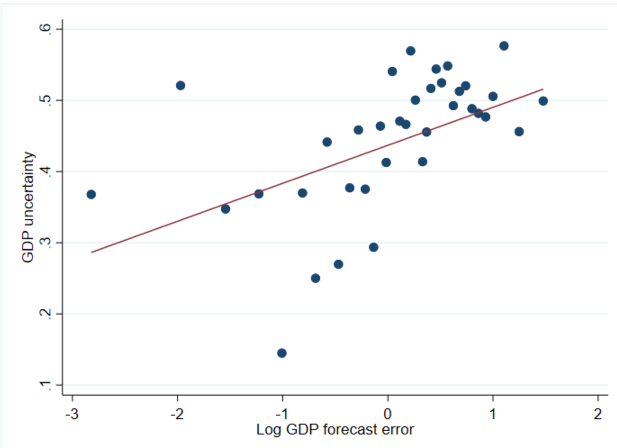
Note: This is the macro growth expectations question from the MES.

Figure 3.3. Businesses Forecasts compared to Professional Forecasters in the Bank of England Survey of External Forecasters

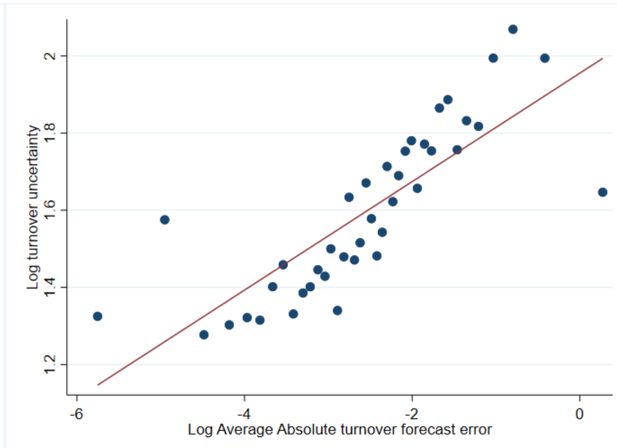


Note: The dark blue bars are the histograms of MES respondents to the macro growth question (see Figure 1). We group the seven bins into four to match the approach of professional forecasters surveyed by the Bank of England (yellow bars).

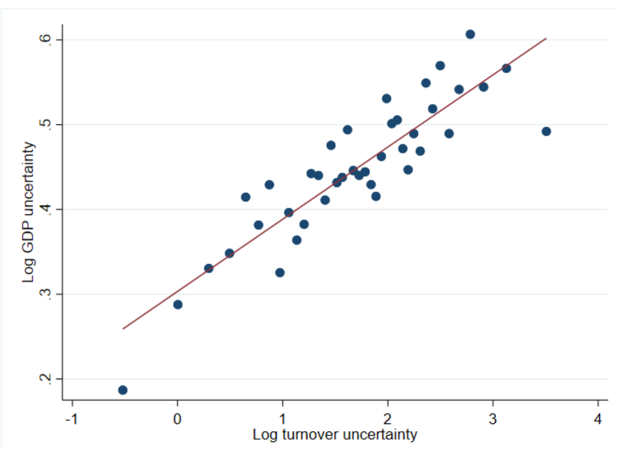
Figure 3.4. Errors and Uncertainty



(a) Panel A. GDP Forecast Errors and GDP Uncertainty



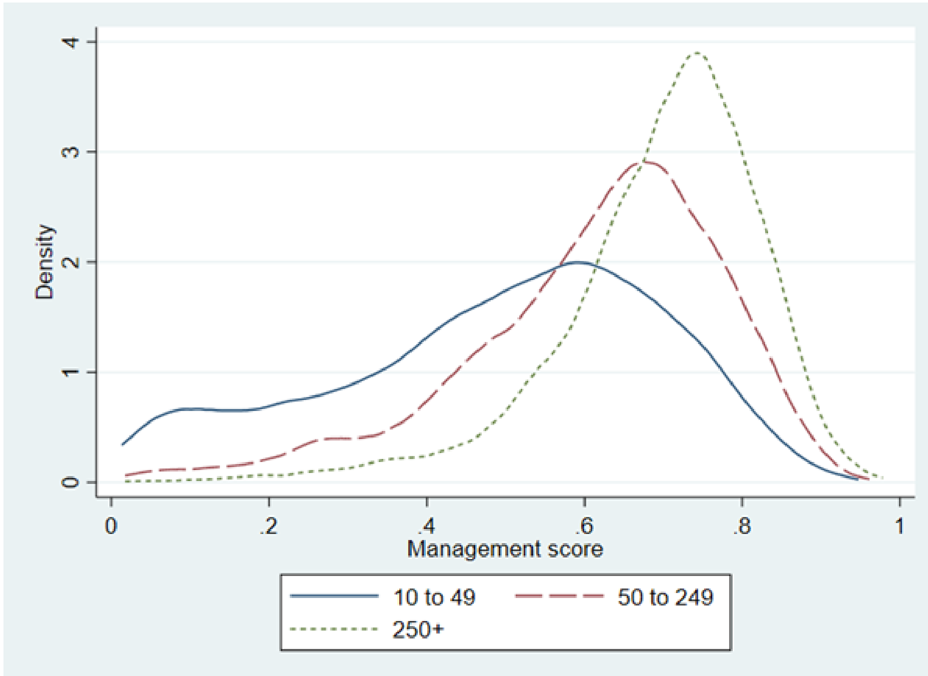
(b) Panel B. Average Turnover Forecast Errors and Turnover Uncertainty



(c) Panel C. GDP and Turnover Uncertainty

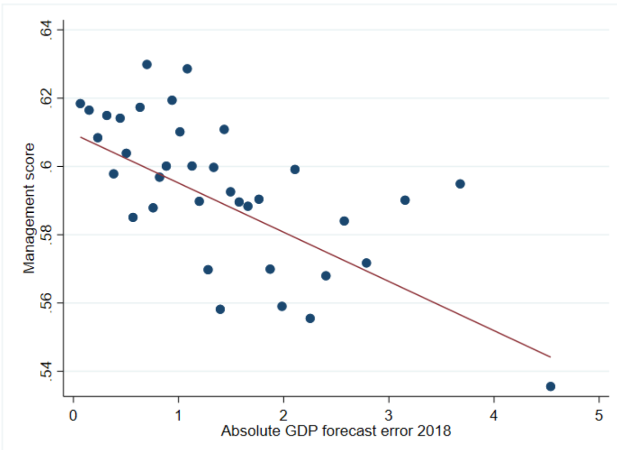
Note: Panel A shows the relationship between log GDP forecast errors and log GDP uncertainty, and Panel B has log average turnover forecast errors and log turnover uncertainty. Panel C shows the relationship between log GDP uncertainty and log turnover uncertainty. Vertical axes show the level of log uncertainty. The values on both axes are winsorized with top and bottom 1% and grouped into 40 equal-sized bins.

Figure 3.5. Firm size and the Management Score Distribution

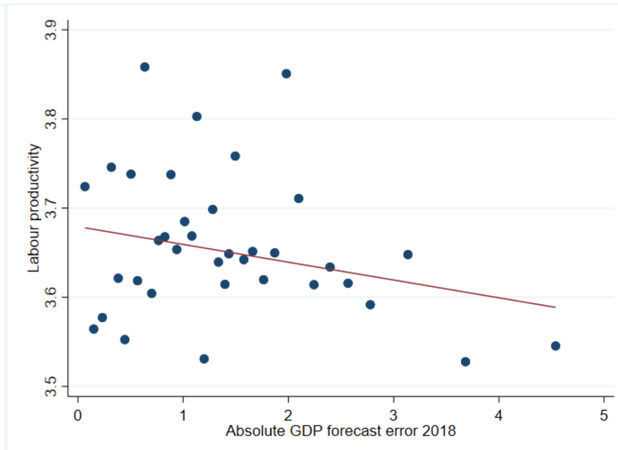


Note: Each curve corresponds to the kernel density of firms in each employment size category.

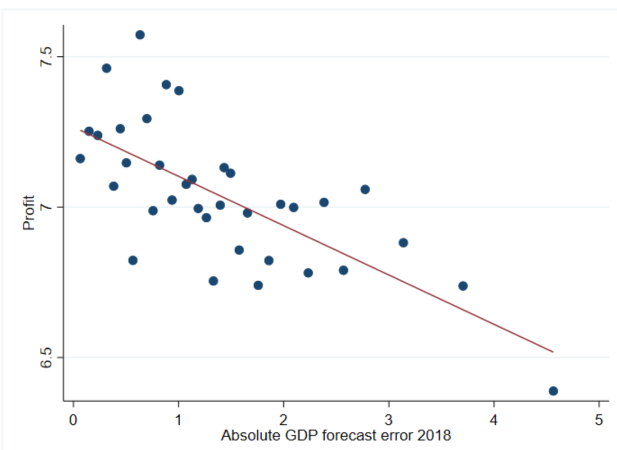
Figure 3.6. GDP Forecast Errors and Management, Productivity and Profits



(a) Panel A. Management Score



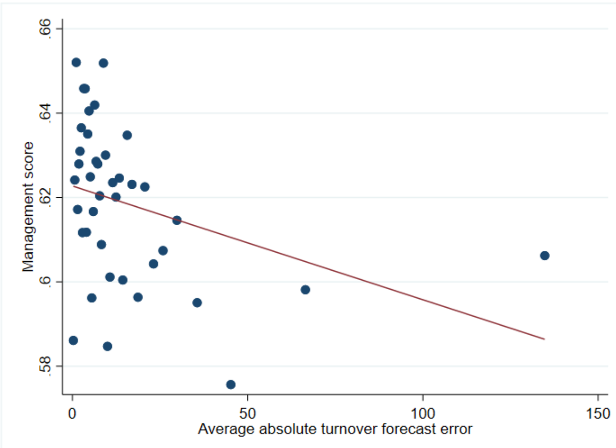
(b) Panel B. Labor Productivity



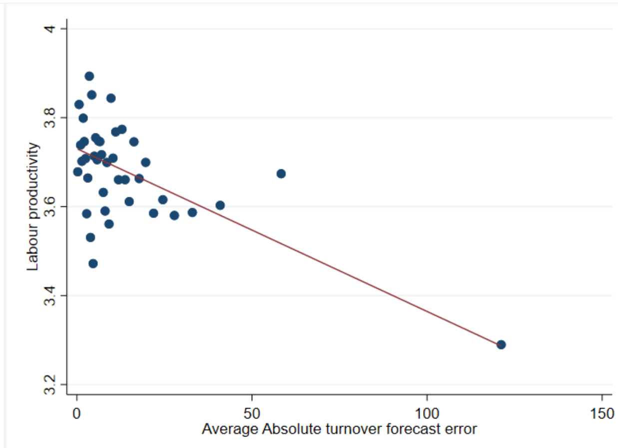
(c) Panel C. Profit

Note: Panel A shows the relationship between absolute GDP forecast errors and management score, Panel B GDP forecast errors and labor productivity, and Panel C GDP forecast errors and log profit. Horizontal axes show the value of forecast errors in absolute. The values are winsorized with top and bottom 1% and grouped into 40 equal-sized bins. Vertical axes are the mean values of management score, labor productivity and profit, respectively, in each panel.

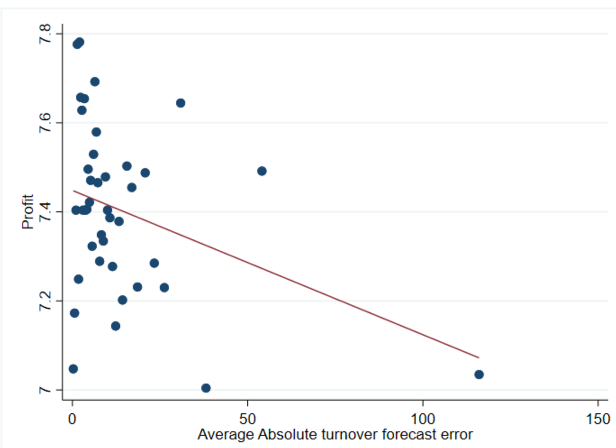
Figure 3.7. Micro Turnover Forecast Errors and Management, Productivity and Profits



(a) Panel A. Management Score



(b) Panel B. Labor Productivity



(c) Panel C. Profit

Note: Panel A shows the relationship between turnover forecast errors and management score, Panel B turnover forecast errors and labor productivity, and Panel C turnover forecast errors and log profit. Horizontal axes show the value of forecast errors in absolute. The values are winsorized with top and bottom 1% and grouped into 40 equal-sized bins. Vertical axes are the mean values of management score, labor productivity, and profit, respectively, in each panel.

Table 3.A1. Correlations Between "Good Response" Dummy and Control Variables

Dependent Variable:	**GDP**		**Turnover**		**Intermediate**		**Capital**		**Employment**	
Dependent Variable:					**Consumption**		**Expenditure**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Management score	0.089***	0.099***	0.109***	0.126***	0.117***	0.127***	0.328***	0.287***	0.246***	0.233***
	(0.0184)	(0.0202)	(0.0208)	(0.0218)	(0.0217)	(0.0236)	(0.0260)	(0.0295)	(0.0238)	(0.0261)
Log employment		-0.006*		-0.007**		-0.007**		0.004		0.003
		(0.0032)		(0.0034)		(0.0037)		(0.0047)		(0.0040)
Log age		0.002		0.004		0.004		0.011		-0.006
		(0.0048)		(0.0053)		(0.0058)		(0.0073)		(0.0059)
Foreign owned		-0.014		-0.040***		-0.039***		-0.046***		-0.064***
		(0.0096)		(0.0115)		(0.0121)		(0.0145)		(0.0129)
Family owned but not family run		0.007		0.010		0.015		0.015		0.007
		(0.0095)		(0.0109)		(0.0114)		(0.0148)		(0.0127)
Family owned and family run		-0.004		0.008		0.006		0.019		0.013
		(0.0074)		(0.0081)		(0.0089)		(0.0114)		(0.0096)
Log GVA per worker		-0.004		-0.006		-0.006		0.016***		0.003
		(0.0040)		(0.0040)		(0.0044)		(0.0058)		(0.0049)
Share of managers with		0.026**		0.021		0.046***		0.051***		0.045***
a college degree		(0.0118)		(0.0130)		(0.0139)		(0.0183)		(0.0162)
Share of non-managers with		-0.011		-0.004		-0.008		-0.008		-0.017
a college degree		(0.0159)		(0.0177)		(0.0189)		(0.0243)		(0.0216)
Industry Dummies	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Location Dummies	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Other Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean of dep. var.	0.920	0.920	0.892	0.892	0.879	0.879	0.786	0.786	0.856	0.856
Observations	7756	7756	7756	7756	7756	7756	7756	7756	7756	7756
R2	0.004	0.184	0.005	0.224	0.005	0.188	0.024	0.178	0.019	0.177

Note: In all columns the dependent variable is a "good response" dummy (see text) for the relevant question. Estimation by OLS with robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Management score is the unweighted average of the score for each of the 12 questions, with scores on a scale of 0 to 1 for each question, where 0 was the least and 1 the most structured management practice. Firm employment is from the ABS in 2016. "Foreign Owned" is a dummy for whether the firm is an affiliate of a non-UK firm. "Family owned and run" is a firm owned by a family and run by a family member; Family owned but not run" is a dummy for a firm which is family owned but whose CEO is a non-family member (a firm which is not owned by a family is the omitted base) from MES. Age is the dated from the date of incorporation from the ABS. Share of managers with a college degree and share of non-managers with a college degree is from MES. Industry dummies are two-digit, location dummies are the 9 NUTS1 regions and "Other Controls" includes dummies for the month when the survey was returned, time spent on the survey, multi-site dummy and reporting accuracy indicator (difference between 2016 employment as reported in ABS and MES).

Table 3.A2. Management GDP Growth Forecasts

Dependent Variable:	**Expected GDP Growth 2017–18**					
	(1)	(2)	(3)	(4)	(5)	(6)
Management score	0.433***	0.371***				0.266***
	(0.0693)	(0.0766)				(0.0842)
Log employment			0.065***			0.049***
			(0.0117)			(0.0130)
Foreign owned				0.042		-0.032
				(0.0392)		(0.0419)
Family owned but not run					-0.047	-0.024
					(0.0452)	(0.0457)
Family owned and run					-0.060**	-0.011
					(0.0307)	(0.0337)
Log age						-0.022
						(0.0203)
Share of managers with						0.035
a college degree						(0.0546)
Share of non-managers with						-0.086
a college degree						(0.0738)
Industry Dummies	No	Yes	Yes	Yes	Yes	Yes
Location Dummies	No	Yes	Yes	Yes	Yes	Yes
Other Controls	No	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	0.105	0.105	0.105	0.105	0.105	0.105
Observations	7134	7134	7134	7134	7134	7134
R2	0.006	0.051	0.052	0.048	0.048	0.055

Note: In all regressions the dependent variable is the expected real GDP growth. Estimation by OLS with robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Management score is the unweighted average of the score for each of the 12 questions, with scores on a scale of 0 to 1 for each question, where 0 was the least and 1 the most structured management practice. Firm employment is from the ABS in 2016. "Foreign Owned" is a dummy for whether the firm is an affiliate of a non-UK firm. "Family owned and run" is a firm owned by a family and run by a family member; "Family owned but not run" is a dummy for a firm which is family owned but whose CEO is a non-family member (a firm which is not owned by a family is the omitted base) from MES. Age is the dated from the date of incorporation from the ABS. Share of managers with a college degree and share of non-managers with a college degree is from MES. Industry dummies are two-digit, location dummies are the 9 NUTS1 regions and "Other Controls" includes dummies for the month when the survey was returned, time spent on the survey, multi-site dummy and reporting accuracy indicator (difference between 2016 employment as reported in ABS and MES).

Table 3.A3. Management and Firm-level Turnover Growth forecast (2016–17)

Dependent Variable:	**2017 Turnover Forecast**					
	(1)	(2)	(3)	(4)	(5)	(6)
Management score	3.974***	6.128***				7.242***
	(1.1078)	(1.2325)				(1.3900)
Log employment			-0.223			-0.378*
			(0.1821)			(0.2124)
Foreign owned				-1.385**		-1.719**
				(0.6361)		(0.6979)
Family owned but not run					0.431	0.379
					(0.6938)	(0.6976)
Family owned and run					0.521	0.561
					(0.4988)	(0.5426)
Log age						-2.288***
						(0.3916)
Share of managers with						1.098
a college degree						(0.8204)
Share of non-managers with						0.198
a college degree						(1.2596)
Industry Dummies	No	Yes	Yes	Yes	Yes	Yes
Location Dummies	No	Yes	Yes	Yes	Yes	Yes
Other Controls	No	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	5.589	5.589	5.589	5.589	5.589	5.589
Observations	6833	6833	6833	6833	6833	6833
R2	0.002	0.060	0.056	0.057	0.056	0.071

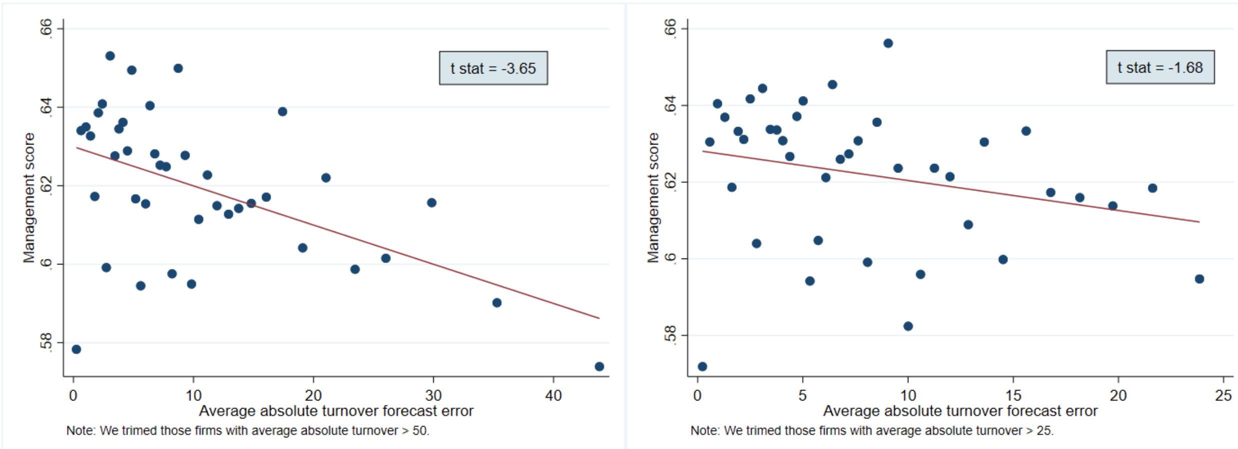
Note: The dependent variable is expected turnover in 2017. Estimation by OLS with robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We exclude firms reporting zero turnover in both MES and ABS from the analysis. Firm employment is from the ABS in 2016. "Foreign Owned" is a dummy for whether the firm is an affiliate of a non-UK firm. "Family owned and run" is a firm owned by a family and run by a family member; "Family owned but not run" is a dummy for a firm which is family owned but whose CEO is a non-family member (a firm which is not owned by a family is the omitted base) from MES. Age is the dated from the date of incorporation from the ABS. Share of managers with a college degree and share of non-managers with a college degree is from MES. Industry dummies are two-digit, location dummies are the 9 NUTS1 regions and "Other Controls" includes dummies for the month when the survey was returned, time spent on the survey, multi-site dummy and reporting accuracy indicator (difference between 2016 employment as reported in ABS and MES).

Table 3.A4. Management and Firm-level Turnover Growth forecast (2016–18).

Dependent Variable:	**2018 Turnover Forecast**					
	(1)	(2)	(3)	(4)	(5)	(6)
Management score	11.678***	13.601***				14.823***
	(1.6498)	(1.8127)				(2.0760)
Log employment			0.160			-0.171
			(0.2624)			(0.3061)
Foreign owned				-2.675***		-3.744***
				(0.9297)		(1.0309)
Family owned but not run					0.012	0.060
					(1.0366)	(1.0386)
Family owned and run					0.922	1.337*
					(0.7013)	(0.7758)
Log age						-3.971***
						(0.5352)
Share of managers with						1.619
a college degree						(1.2502)
Share of non-managers with						0.774
a college degree						(1.7682)
Industry Dummies	No	Yes	Yes	Yes	Yes	Yes
Location Dummies	No	Yes	Yes	Yes	Yes	Yes
Other Controls	No	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	7.029	7.029	7.029	7.029	7.029	7.029
Observations	6833	6833	6833	6833	6833	6833
R2	0.009	0.069	0.059	0.060	0.060	0.084

Note: The dependent variable is expected 2018 turnover. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Employment from ABS in 2016. We exclude firms reporting zero turnover in both MES and ABS from the analysis. "Foreign Owned" is a dummy for whether the firm is an affiliate of a non-UK firm. "Family owned and run" is a firm owned by a family and run by a family member; "Family owned but not run" is a dummy for a firm which is family owned but whose CEO is a non-family member (a firm which is not owned by a family is the omitted base) from MES. Age is the dated from the date of incorporation from the ABS. Share of managers with a college degree and share of non-managers with a college degree is from MES. Industry dummies are two-digit, 9 NUTS1 location dummies and "Other Controls" includes dummy for month when survey returned, time spent on survey, multi-site dummy and reporting accuracy indicator* p ¡ 0.10, ** p ¡ 0.05, *** p ¡ 0.01. Standard errors are in parentheses

Figure 3.A1. Sensitivity of the Turnover Forecast Error and Management Score Relationship to Trimming Outliers



(a) Panel A. Trim above 50

(b) Panel B. Trim above 25

Note: Both panels show the relationship between turnover forecast errors and management scores. Panel A trims the sample with forecast errors equal or greater than 50% and Panel B trims the sample with forecast errors equal or greater than 25%. Horizontal axes show the level of the forecast error in absolute value. The values are winsorized with top and bottom 1% and grouped into 40 equal-sized bins. Vertical axes are the mean values of management score. The box in both panels shows t statistics.