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Capital Investment, Technology Switching and Production after A Natural Disaster*

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Abstract

This study analyzes the effects of natural disasters on capital investment and production. We examined the impact of the 2011 Great East Japan Earthquake, the fourth largest earthquake ever recorded worldwide, on the fishing industry. Rich administrative data from the fishing industry allowed us to identify the impact on output, labor input, capital reinvestment and technology switching caused by the severe damage to fishing facilities and equipment from the tsunami waves. The results show that immediately after the earthquake, the number of fishing boats and sales decreased by 60%. Five years later, the number of boats was still lower by 20% and sales were down by 11%. The negative effects persisted even after 10 years. We also found that high-productivity fishers tended to adopt new fishing technologies due to the reduction in switching costs caused by government financial aid, but we did not find a similar effect for low-productivity fishers.

Keywords: Natural disaster, capital investment, economic shock, natural experiments, fishing industry
JEL classification: D22, E22, O33, Q54

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1 Introduction

Natural disasters affect economic activities by injuring people and damaging buildings and infrastructure. According to the Emergency Events Database (EM-DAT), the number of natural disasters has increased in recent decades. This increase may be attributed in part to more accurate reporting, but is also associated with global warming and population growth, which has made extreme natural events and damage to humans increasingly likely(Strömberg, 2007). For example, the EM-DAT shows that 10–100 thousand people are killed every year by geophysical or hydrometeorological events, affecting approximately 100 million people.

The literature indicates that natural disasters similarly affect a broad range of economic activities. For example, hurricanes reduce labor supply in damaged areas while increasing labor supply in neighboring areas (Belasen and Polachek, 2009; McIntosh, 2008). They also negatively affect the labor market outcomes of evacuees (Groen and Polivka, 2008), although such negative impacts may be transitory (Deryugina et al., 2018). Exposure to natural disasters hinders human capital accumulation (Caruso, 2017; Cuaresma, 2010), and the inflow of evacuees influences incumbent students (Imberman et al., 2012). Sometimes, severe disasters trigger out-migration and decrease land and housing values (Boustan et al., 2012, 2019). However, Hornbeck and Keniston (2017), studying the Great Boston Fire in 1872, found an increase in land prices, attributed to efficient urban redevelopment or creative destruction.

The impact of natural disasters on economic growth has been investigated mainly through cross-country analyses, which have not reached a consensus. Felbermayr and Groschl (2014), Hsiang and Jina (2014), and Noy (2009) found a negative impact on GDP growth, whereas Skidmore and Toya (2002) found a positive one. The positive impacts of disasters are creative destruction and the market-cleansing effect; capital destruction facilitates an upgrade of legacy capital, and damage from disasters leads low-productivity firms to exit the market. The consequences of natural disasters depend on their severity and how they affect the economic sector. The negative impact may be limited to extremely severe disasters, the agricultural sector being particularly vulnerable to them (Cavallo et al., 2013; Loayza et al., 2012). While much of this literature relies on cross-country (panel) data, Barone and Mocetti (2014) conducted a case study using two earthquake events in Italy, finding a negative long-run impact on regional GDP per capita in one case, but a positive impact in the other. They attributed this discrepancy to institutional quality, as it affects how efficiently financial aid is used.

Evidence of direct impact of natural disasters on firm activity is limited in the literature. Cole et al. (2019) used plant-level data combined with detailed damage intensity data and found that the Great Hanshin-Awaji earthquake decreased the probability of survival while increasing the productivity of surviving firms.[1] Okazaki et al. (2019) used historical data to evaluate the impact of the 1923 earthquake in Japan on manufacturing firms and found similar results and capital upgrades among surviving firms. Hosono et al. (2016) show that investment in undamaged firms is suppressed when their main banks are damaged by the earthquake. Furthermore, De Mel et al. (2012) found through field experiments after the 2004 tsunami in Sri Lanka that the recovery of micro-enterprises was hindered by a lack of access to capital, making relief aid was essential. Noth and Rehbein (2019) found that the flood in Germany improved the turnover and leverage ratio of the firms in damaged area.

Our study adds new evidence to the literature on natural disasters, a case study of the 2011 Great East Japan Earthquake with a focus on the fishing industry. The Great East Japan Earthquake was the fourth largest earthquake in the world since 1900 and the largest recorded in Japan. A distinguishing feature of this disaster is the disastrous tsunami waves triggered by the earthquake. As a result, the Pacific coastal areas of Japan, particularly Iwate, Miyagi and Fukushima prefectures, were severely damaged. The fishing industry was one of the most severely affected industries, with most fishing boats and equipment washed away by the tsunami waves.

Our empirical analysis draws on detailed fishing-port-level data. The data includes the number of boats, amount of fish landings, and sales by fishery and fish types, allowing us to analyze the fishery production process at the port level. We conducted a prefecture-level difference-in-differences (DID) analysis with a treatment group consisting of Iwate and Miyagi prefectures.

The estimation results show that the impact of the earthquake was disastrous in 2011 and recovery was stagnant. The number of registered boats decreased by 60% in 2011, and more than 20% of the losses continued even five years after. Ten years after the earthquake, approximately 10% of the losses remained. Furthermore, the negative impact on the number of fish landings was significant, recording a decrease of 70% and 36% in 2011 and 2016, respectively, with negligible recovery thereafter. Since the damaged prefectures had a relatively large share of the fishing industry, the decreased fish supply was followed by a price surge. However, the price increase did not fully offset the damage, and sales were lower by more than 20–30% even 5–10 years after the disaster.

Additionally, we analyzed the heterogeneous impact based on the severity of damage, as the net impact of the disaster is determined by both the direct negative effects of the disaster and positive aspects such as creative destruction and the market-cleansing effect. We found that, even among ports with limited damage from tsunami waves, the total landed amount decreased by 20% in the long run, whereas sales remained unaffected in the long run. However, in ports severely damaged by the tsunami waves, both the total

[1] Tanaka (2015) found a negative impact on the value-added, using the same plant-level data and event but without detailed damage intensity data.

landed amount and sales decreased by approximately 40% in the long run. Moreover, sales per fisher declined by 20–30% in these ports. Therefore, we found no evidence of a net positive effect of the disaster, regardless of the severity of the damage, and severely damaged ports continued to experience a negative impact on productivity.

We also examined heterogeneity by port-level productivity. We found that recovery from the disaster was quicker in high-productivity ports than in low-productivity ports. In the long run, the recovery of low-productivity ports caught up with the high-productivity ports in terms of number of boats and fishers, and sales. Therefore, we did not find evidence of a market-cleansing effect in the long run, probably due to the generous financial aid from the government helping low-productivity fishers to continue operating. However, we find substantial heterogeneity in fish landings and prices. While the landing amount recovered to 80–100% in high-productivity ports, the recovery was limited to 50% in low-productivity ports. Because fish from low-productivity ports are mostly traded in the local market, it results in a substantial increase in fish prices due to the demand-supply mechanism. By contrast, fish from highly productive ports tend to be traded nationwide, and their supply shock seems to be absorbed by fish from other regions, thereby limiting price increases.

Finally, we investigated whether the devastating disaster caused technology switching, as the tsunami washed away most of the fishing boats and equipment, and whether the government provided generous subsidies for capital reinvestment. We utilized the detailed information on fishing methods and found that highly productive fishers adopted new fishing methods, whereas less productive ones did not. This suggests that natural disasters cause creative destruction, particularly among high-productivity ones.

This study makes three contributions. First, we add new evidence of the impact of disasters on firm activities using a unique fishing industry dataset. In line with the cross-country analysis by Loayza et al. (2012), we provide empirical evidence of the disastrous impact of the Great East Japan Earthquake on the fishing industry. Considering that the Great Hanshin-Awaji earthquake in Japan positively affected the surviving plants in the manufacturing industry (Cole et al., 2019), our results suggest substantial industrial heterogeneity, even within a single country. Thus, analysis using aggregated data from previous studies may have masked the heterogeneity in the impact of natural disasters. Second, to our knowledge, this study is the first to find that the pricing mechanism alleviates damage to firms. Cavallo et al. (2014) and Gagnon and Lopez-Salido (2019) found negligible response of supermarket prices despite increase in demand or decline in supply, in sharp contrast to our results. Third, our analysis reveals that the natural disaster prompted technology adoption among high-productivity fishers, while low-productivity fishers did not experience similar changes. This finding helps to clarify the lack of consensus in the literature regarding the market cleansing and creative destruction effects. Our analysis implies that generous policies can support highly productive firms in recovering and becoming more efficient through technology adoption. However, these same policies may enable low-productivity firms, which would likely otherwise exit the market, to continue operating. Therefore, although access to financial aid after a disaster is essential for recovery (De Mel et al., 2012), overly generous subsidies can harm economic efficiency.

Our study also relates to the literature on the Great East Japan Earthquake. For example, Genda (2014); Higuchi et al. (2012); Yamasaki et al. (2016) investigated the direct impact on labor supply. Kondo (2018) studied the impact on labor supply through supply chain disruptions. Sugano (2016) examined the well-being of elderly victims. Akesaka (2019); Hanaoka et al. (2018) analyzed the impact on risk and time preferences. Tajima et al. (2016) estimated the hedonic price function of vegetables using radiation exposure due to the Fukushima Daiichi nuclear disaster and found a more than 10% decrease in prices. Similarly, Kawaguchi and Yukutake (2017) found a negative impact of radioactive contamination on residential land prices. Carvalho et al. (2016) revealed the propagation of negative impacts on firm outputs through the supply chain. While their analysis focused on the short-run indirect effects on undamaged firms(up to 2012), our study investigates the long-run outcomes of directly damaged industries. To our knowledge, this is the first study to evaluate the causal impact of the Great East Japan Earthquake on the fishing industry.

2 The Great East Japan Earthquake

The earthquake on March 11, 2011, off the Pacific coast of the Tohoku region, registered a magnitude of 9.0. On April 1, 2011, the Cabinet Office named it the "Great East Japan Earthquake" because of the immense scale of the disaster, which had wreaked havoc across eastern Japan. The earthquake caused building collapse and fires, and unprecedented tsunami waves causing widespread inundation and nuclear power plant accidents. In particular, the three prefectures of Iwate, Miyagi, and Fukushima were severely affected by tsunami waves as they faced the Pacific coast in the Tohoku region. Tsunami waves reached heights of 8.5 meters in Miyako City (Iwate Prefecture), 14.8 meters in Onagawa City (Miyagi Prefecture), and 9.3 meters in Souma City (Fukushima Prefecture), with a total inundation area of 561 km^2. The tsunami caused meltdowns in nuclear power plants in Fukushima Prefecture. (See Figure A1 for the geographical distribution of the damage.)

The earthquake resulted in approximately 20,000 fatalities and 6,000 injuries. According to the National Police Agency, 90% of the deaths were due to drowning, underscoring the severity of the impact. Housing was also badly affected, with approximately 130,000 houses collapsing and 260,000 partially damaged. Due to the destruction of infrastructure and nuclear contamination, the number of evacuees immediately after the earthquake exceeded 450,000. Most evacuees resided in temporary housing provided by the government within their home prefectures, although many from Fukushima had to evacuate to other prefectures because of nuclear pollution.

In anticipation of the extensive damage, the Japanese government established a task force to address the crisis. The Emergency Response Office was established at the Prime Minister's Office to assess the extent of the damage, ensure resident safety, provide evacuation instructions, secure essential services, and disseminate information. Given the scale of the disaster, the government designated it an extreme disaster under the Extreme Disaster Act, which allowed financial assistance for recovery efforts. In addition to domestic aid, 159 countries and regions along with 43 institutions offered assistance, and teams of aid workers and experts were dispatched from 28 countries, regions, and institutions.

In 2011, a supplementary budget amounting to approximately 1% of the GDP was allocated for urgent recovery efforts. This budget covered expenses such as disaster waste disposal, loans for small- and medium-sized businesses, and financial support for local governments. Notably, the cost of restoring sewers, beaches, roads, and fishing ports constituted 25% of the budget. The government established a 10-year reconstruction timeline for earthquake recovery. The five years following the disaster (2011 to March 2016) were designated as the intensive reconstruction period, during which infrastructure was significantly developed, including temporary housing for disaster victims and disaster waste removal and disposal. The latter five years of the recovery period were designated for reconstruction and development, focusing on reopening railways, supporting the return of evacuees, and attracting international events such as the Olympics. According to a report from the Reconstruction Agency, approximately 35 trillion JPY was earmarked for reconstruction-related budgets between 2011 and 2018, with debris disposal completed, and the number of evacuees decreased from approximately 470,000 in 2011 to 48,000 in 2020.

The earthquake significantly affected the fisheries sector. According to the 2010 Annual Statistics of Fishery and Fish Culture, prefectures along the Pacific coast that were severely affected constituted a thriving fishing region, accounting for 21% of the national fishery and mariculture industry. The total damage to fisheries-related facilities exceeded one trillion JPY, with Miyagi, Iwate, and Fukushima Prefectures accounting for 91% of this damage. In addition to production-related losses, fishers' cooperatives in the affected areas reported 768 deaths among members and employees.

Fishing-related damage extends from fishing grounds to boats and aquacultural systems. Specifically, 319 fishing ports were damaged by tsunami waves and land subsidence, with 78% located in Iwate and Miyagi prefectures. The tsunami affected approximately 28,000 fishing boats, primarily small coastal vessels, with rock fishing particularly popular in these regions. The disaster destroyed mariculture facilities and fish tanks, cargo handling areas and fueling facilities, and led to operational shutdowns due to debris and adverse effects on the ecosystem. The majority of the damage to the fishing industry was concentrated in Iwate and Miyagi prefectures, leading to substantial impairment of port infrastructure and the capital necessary for fishing and aquaculture.

The Japanese government provided reconstruction support in response to damage to fisheries. In 2011, supplementary budget of 734 billion JPY was allocated to aid the reconstruction of the fishing industry, covering the restoration of fishing ports and villages, payment for fishing boat insurance and fishers' mutual aid, and interest-free loans. Similar to overall recovery support, the recovery period for the fishery sector was set at 10 years. The first five years, when reconstruction demand was anticipated to peak, was designated as an intensive reconstruction period. The government worked diligently to clear debris from fishing grounds and ports, subsidize the costs of installing fishing-related equipment, and improve mariculture facilities. Specifically, it implemented policies to support fishing boat insurance payments and subsidized two-thirds of the cost for fishing cooperatives to purchase boats and fixed nets, while reducing the burden of the remaining one-third through interest-free loans.

3 Data

Our analysis draws on the Topography of Fishery Ports 1989–2020 (*gyo-ko kousei* in Japanese), based on an annual survey conducted by the Japanese Fisheries Agency. This survey covers all fishery ports in Japan, with the prefectures or municipalities responsible for managing these ports collecting and reporting information on the number of fisheries and fishing boats registered or used in each port, as well as the number of catches and sales. Thus, the survey serves as a valuable tool for investigating the production process by facilitating the measurement of labor input, capital input, and outputs.

Considering that the tsunami waves washed away many boats, the number of boats provides important insights into the magnitude of the damage and the dynamics of capital investment following the disaster. Production input and output information allows us to analyze port productivity. Furthermore, the survey collected data on the number of fish landings and sales for each fishing method (57 methods) and fish type (165 types), enabling us to examine production-switching behavior.

For our main analysis, we aggregated all ports except those on isolated islands to facilitate interpretation, as most ports in the primarily damaged prefectures —Iwate, Miyagi, and Fukushima—are not located in the excluded areas. We also excluded the ports in Fukushima Prefecture for two reasons. First, interpretation of the analysis results is complicated because of nuclear pollution and the resulting displacement of many residents. Second, the fishing industry in Fukushima is significantly smaller than that in Iwate and Miyagi.[2] Finally, because the objective of this study was to investigate

[2]We conducted the analysis using the ports in Fukushima Prefecture, and our results were robust to this sample restriction.

the impact of the tsunami, we excluded ports that do not face the open sea, leaving us with data from 39 prefectures. In our main analysis, we aggregated the input and output measures to construct prefecture-level panel data.

Because the ports in Iwate and Miyagi had suffered severe damage, some of them did not respond to the survey between 2011 and 2013. In 2011, the survey was not conducted in Iwate, Miyagi and Fukushima prefectures. In 2012 and 2013, approximately 38% of the ports in Iwate and Miyagi did not respond to the survey (Panel (a) in Figure A2), and smaller ports were more likely to have unreported records (Panels (b) and A2). Because the survey collected information from the previous year, we do not have any data for 2010 and some data for 2011 and 2012 are missing. Because missing values are not counted when the data are aggregated at the prefecture level, the estimation results for these years require careful interpretation. We confirmed the robustness of our analysis by excluding those ports from the analysis sample.

3.1 Descriptive Analysis

Column 1 of Table 1 presents an overview of the Japanese fishing industry in terms of production inputs and outputs during the sample period between 2000 and 2020. Most fishers are engaged in coastal fisheries. In fact, 87% of the boats weighed less than 5,000 kg, and the number of boats per fisher, or capital equipment rate, was 0.79. Our data include the number of boats actively used for fishing. Using this information, we calculated the capital utilization rate and found that most registered boats were actively used in production. The remaining rows of Table 1 present production output measures in terms of landed weight, sales, sales per kilogram, and sales per fisher.

Columns 2 and 4 tabulate the information before the earthquake for Iwate and Miyagi prefectures as well as for other prefectures separately. A comparison of these two columns shows that the fishing industries in Iwate and Miyagi are substantially larger than those in other prefectures. For example, these two prefectures have approximately three times as many boats and average sales more than three times that in the other prefectures, with a much larger number of fishers.

However, after the earthquake, the fishing industries in Iwate and Miyagi prefectures have experienced substantial downsizing, losing approximately half their fishing boats and a quarter of their fishers, leading to a substantial decrease in output. Although the Japanese fishing industry has suffered from a long-term downsizing trend, as shown in Columns 4 and 5 and Figure 1, the sharp decline in production inputs and outputs in these two prefectures is notable and stands out from the long-term trend. Sales per kilogram, which we consider as price, increased from 183 JPY to 229 JPY after the earthquake. The tremendous negative shock from the earthquake and tsunami was partially absorbed by this price increase. Thus, despite the huge decline in the number of catches, the decline in sales was relatively small.

Figure 1 shows the long-term trends of our input measures. As the size of the fishing industry varies significantly by prefecture, we normalized the data based on the 2009 value, the most recent pre-earthquake year available. This figure highlights three important aspects of the fishing industry. First, the Japanese fishing industry has generally downsized. In prefectures not severely affected by the earthquake, the number of boats decreased by approximately 40, and the number of fishers fell by 45% over the last two decades. However, the capital equipment and capital utilization rates remained stable or even increased slightly over time. Second, despite the large differences in the size of the fishing industry between Iwate and Miyagi prefectures and other prefectures, their trends were comparable from 2000 to 2009. Finally, we observed the drastic impact of the earthquake on Iwate and Miyagi, with sluggish recovery from the damage. The data show that these prefectures lost 60% of their fishing boats after the earthquake, and even after 10 years, the number of boats remained at approximately 70% of the 2009 level. Although the decline in the number of fishers appears moderate in comparison, a 30% drop was recorded in 2012. As a result, the capital equipment rate also declined and remained far from recovery even 10 years after the earthquake.

Figure 2 shows the long-term trends in our output measures. Compared with the trends in the number of boats and fishers, the decreasing trends in output are somewhat moderate, and we confirm Iwate and Miyagi prefectures have similar trends to the other prefectures. Similar to the inputs, we observe a sharp decrease in the landed amount of fish and sales, as well as in per capita sales, after the earthquake. While the outputs recovered until 2014, they stagnated thereafter. By contrast, we found a 35% increase in the price in the year of the earthquake, which is presumably due to the supply shortage of fish. To summarize, Figures 1 and 2 suggest that the fishing industry in Iwate and Miyagi prefectures show a decreasing trend comparable to the other prefectures, they suffered substantially from the earthquake, and their recovery was rather stagnant.

4 Effects on the inputs and outputs of fishery production

4.1 Empirical model and identification strategy

To understand how the earthquake affected the fishery production in Iwate and Miyagi prefectures, we estimate the standard dynamic DID model.

$$y_{jt} = \sum_{\substack{s=2000 \\ s \neq 2009}}^{2016} \beta_s D_j \times 1\{t = s\} + x'_{jt}\gamma + \theta_j + \eta_t + u_{jt}, \tag{1}$$

where j and t indicate prefecture and year, respectively; θ_j is the prefecture fixed effect; and η_t is the year fixed effect. The treatment status, D_j, takes the value of one for Iwate and Miyagi prefectures and zero otherwise. As discussed earlier, Fukushima prefecture was excluded from the analysis for ease of interpretation. Vector x_{ijt} includes region-specific linear trends.[3] To analyze the impact on production inputs, we used, as the dependent variable, y_{jt}, the log of the number of boats, number of fishers, number of boats per fisher, and fraction of boats actually used (i.e., capital utilization rate), all of which are aggregated at the prefecture level. For the output measures, we used the log of the total landed weights, total sales, total sales per fisher, and ratio of total sales and total landed weights which is regarded as "average price" for the fish.

The standard parallel trend assumption is a key identification assumption for assessing the causal impact of a disaster. This assumption posits that the growth rates of production inputs and outputs in the two treated prefectures would have followed the same average growth rates as those in the other prefectures in the absence of a disaster. In equation (1), the parameter of interest is β_s, which is interpreted as the impact of the Earthquake on fishery ports for $s \geq 2011$, whereas β_s is expected to be zero for $s \leq 2008$ under the parallel trend assumption. Note that the baseline year is set to 2009, as opposed to 2010 because the survey was not conducted in Iwate and Miyagi in 2011. As the survey collected information in the previous year, we do not have the information for 2010.

In addition to the parallel-trend assumption, we require additional assumptions that could potentially be violated. First, equation (1) assumes that prefectures other than Iwate and Miyagi did not suffer from the disaster, although adjacent prefectures such as Aomori and Ibaraki were affected. However, as discussed in Section 2, the damage to the fishing industry was mostly concentrated in Iwate and Miyagi prefectures. Furthermore, if those control prefectures were also negatively affected by the disaster, we would underestimate the true impact in magnitude; thus, our estimate still serves as the lower bound.

The second assumption is the Stable Unit Treatment Value Assumption (SUTVA). Although SUTVA is usually taken as a given in many empirical analyses, it may be violated in our analysis because of a general equilibrium effect. Since Iwate and Miyagi prefectures play an important role in the Japanese fishing industry, changes in their fish supply can affect the price of fish, which in turn affects the supply of fish from other prefectures. In this case, we could over-estimate the effect on the total landed amount and total sales. Although it is difficult to check the extent to which the violation of the SUTVA matters in our analysis, we emphasize that the general equilibrium effect occurs only when these two prefectures were substantially negatively affected in the first place.

[3] We used the two regional classification: eastern Japan (Hokkaido, Tohoku, Kanto, and Chubu) and western Japan (Kinki, Chugoku, Shikoku, and Kyusyu).

Finally, when we interpret the estimation result of equation (1), we report $\exp\left(\hat{\beta}_s\right) - 1$ instead of $\hat{\beta}_s$ because the effect size is sometimes too large for a log point change, β_s, to be a good approximation of the percentage change. Thus, we used the exact formula, $\exp\left(\hat{\beta}_s\right) - 1$, for the "percentage change" interpretation when the dependent variable is log-valued and the explanatory variable is binary.

4.2 Estimation results

Figure 3 summarizes the estimation results of equation (1) for the capital and labor inputs. Figure 3a illustrates the substantial damage to fishers. The earthquake and subsequent tsunami waves affected approximately 60% of the boats in Iwate and Miyagi prefectures. Although the number of boats gradually recovered, this recovery was far from complete; in fact, $20\%(= 100 \times 0.12/0.58)$ of the initial negative impact remains even 10 years after the earthquake. The estimation results imply that the generous government aid measures were not sufficient to fully restore the number of boats.

Considering that the fishing industry in Japan has shrunk over time and that elderly individuals are overrepresented in this sector, an elderly fisher who has lost a boat may choose to retire rather than reinvest in a new one. Figure 3b shows that the number of fishers decreased after the earthquake. Although the negative impact did not peak immediately after the earthquake, this may be because we measured the number of fishers *registered* with a fishery cooperative, rather than *active* fishers. Given the aftermath of the earthquake, it is reasonable to assume that they needed time to decide whether or not to deregister. The negative impact peaked in 2013, with approximately 30%of fishers leaving the industry, although this estimate is not precise. In 2014 and afterward, the negative impact persisted but at a reduced magnitude of approximately 10%Therefore, compared to the impact on capital input, the impact on labor input was relatively moderate, while the magnitude of their persistent negative impacts after 10 years is still non-negligible, at approximately 10% for both.

From Figures 3a and 3b, we observe that both the capital and labor inputs were negatively affected by the disaster and did not completely recover in long run. How was the capital-equipment rate affected? If we consider a simple static firm profit maximization problem with constant elasticity of the substitution production function in a competitive market, the capital equipment rate should be constant. The yearly trends of the capital equipment rate demonstrate that it was almost constant over time before the disaster (Figure 1d). As we cannot observe all capital inputs, we approximate the capital equipment rate using the number of boats per fisher. Although the capital equipment rate decreased by 61% after the earthquake mainly due to the loss of boats, the capital equipment rate was recovered relatively quickly (Figure 3c). Indeed, the negative impact was 25% in the following year, and the capital equipment rate recovered completely after 10 years. Therefore, while the fishing industry downsized, fishers seemed to have reinvested sufficiently to obtain the optimal level of capital.

Finally, we analyzed the impact on the capital utilization ratio, measured by the fraction of boats used for fishing. The impact on the capital utilization rate was not felt immediately after the earthquake but one year later. In 2012, capital utilization decreased by 8%, and this negative effect tended to decrease over time, although the estimates were imprecise. Ten years after, the negative impact had decreased to 2%. Given the small long-run impact, production activity seems to have almost recovered enough to fully utilize ethe retained boats.

Figure 4 shows the tremendous negative impact of the disaster on the fishing industry. The total landed amount declined by 71%, and sales declined by 62% in 2011 (Panels (a) and (b) in Figure 4). Although these outcomes gradually improved by 2014, we found no recovery thereafter. The negative impact on sales tends to be smaller than that on landed amounts, which is attributed to price changes. The price increase of 29% in 2011 is notable, and we suspect this is due to the well-established brands of fishing products in Iwate and Miyagi prefectures, coupled with a supply shortage immediately after the earthquake, which led to a spike in prices. Furthermore, the increase in price tended to persist, with a magnitude of 10–15% until 2018, which diminished in 2019 and 2020. Finally, we observed a negative impact on per-capita output (Panel (d)). As expected, it sharply decreased in 2011, but interestingly, recovered to approximately -15% in 2012 and remained stable until 2016; this negative impact became smaller in the long run. In comparison, the negative long-run impact on sales is much larger than that on per-capita sales, suggesting that a large part of the decline in sales can be attributed to the downsizing of the industry, rather than a decline in productivity.

In terms of the coefficients for the pre-treatment year, we did not find any statistically significant estimates in Figures 3 and 4 in most cases. Although a parallel pre-trend does not necessarily imply a parallel post-trend, these estimation results suggest that the trends of the treated prefectures are closely aligned with those of other prefectures. However, we find some negative coefficients in the pre-treatment years for sales and per capita sales (Figures 4b and 4d). To further verify the robustness of our results, we run this analysis using the synthetic control method (Abadie et al., 2010). To apply this method, we aggregated Miyagi and Iwate by taking the average, with the donor consisting of 32 prefectures with coastlines, excluding Aomori, Ibaraki, Chiba, and Osaka prefectures.[4] To construct a synthetic control, we used data from 1989 to 2009. Figures A5 and A6 show almost the same effects as those of the DID estimates.[5]

Another concern is the non-reporting issue during 2011 and 2013, since the outcomes

[4] Aomori, Ibaraki, and Chiba prefectures were excluded because these were also damaged by the tsunami. We excluded Osaka prefecture because of missing values of registered boats in 2007 and of sales in 2015.

[5] See Table A1 for the weights of synthetic control for each dependent variable.

are treated as zero for ports that did not report when the data are aggregated to the prefecture level, which could result in an overestimation of the magnitude of the impact. To confirm that this is not a serious concern, we reestimated equation (1) by excluding ports that never reported anything during 2011 and 2013 from the analysis sample throughout the sample period; thus, the outcomes of those ports are always treated as zero, regardless of the year. Figure A3 and A4 show virtually the same results as our baseline results. Thus, our findings are not driven by the non-reporting issue.

5 Mechanism

5.1 Heterogeneous effects by the severity of damage

The severity of the damage is an important source of heterogeneity. Some studies argue that natural disasters have a positive impact on economic growth (Skidmore and Toya, 2002; Barone and Mocetti, 2014) because of creative destruction and market-cleansing effects. Okazaki et al. (2019) found evidence of capital upgrading after a disaster. However, the net effect of disasters is determined by both the potential positive aspects and the direct damage caused by the disaster. In addition, the degree of creative destruction and market cleansing may depend on the severity of the damage. However, previous studies have not analyzed this heterogeneity.

The Great East Japan Earthquake is a good case for studying the heterogeneous effect of natural disasters on production activity, as tsunami damage is widespread in Pacific coastal regions, with substantial variation in the height of tsunami waves (Figure A1). To analyze such heterogeneity, we merged the tsunami height data collected by the 2011 Tohoku Earthquake Tsunami Joint Survey (TTJS) Group with port-level data using the geographic information system (GIS). Then, we divided the damaged ports into three groups by tertile of the tsunami height and estimated the following equation for each group with undamaged ports as a control group, as follows:

$$y_{it} = \sum_{k=1}^{3} \sum_{\substack{s=2000 \\ s \neq 2009}}^{2016} \beta_s^k Damage_i^k \times 1\{t = s\} + x'_{ijt}\gamma + \theta_i + \eta_t + u_{it},$$

where $Damage^k$ indicates the k-th tertile group and x is the same vector of covariates as in equation (1). In the estimation, the total number of fishers in each port in 2009 was used as the weight. The treatment status was assigned based on the height of the tsunami waves, including ports in prefectures other than Miyagi and Iwate.

Figure 5 shows the estimation results for production inputs. As expected, the immediate impact of the disaster on the number of boats differed substantially between the 1st and the 3rd tertile groups. The negative impact on the 1st tertile group was limited to a

10% decrease in the number of boats, which dissipated the following year. However, the negative impact persisted in the 3rd tertile group, and even 10 years after the disaster, the number of boats remained 10% lower. Although the estimates were noisy, we found heterogeneous effects on the number of fishers. In the 3rd tertile group, the number of fishers decreased by 10%, whereas it increased in the 1st tertile group. Consequently, despite the large negative impact on the 3rd tertile group, the capital equipment rate recovered to its original level in the long run. By contrast, we found no significant effects on the capital utilization rate.

Figure 6 shows the estimation results for production outputs. Although the impact on production input was limited to the 1st tertile group, we found a sizable effect on production output. The landed amount declined by approximately 35% in 2011, and this decline remained persistent. Ten years after the disaster, the total land area decreased by 20%. In terms of sales, because the long-run negative effect on the landed amount was offset by price increases, we did not find a significant negative effect on sales in the long run for the 1st tertile group. The long-run impact on sales per fisher was negative, although not statistically significant at the 5% level in the mid- and long-run. Therefore, even among ports where disaster damage was not severe, we did not find any evidence of an increase in production outputs.

In contrast to the 1st tertile group, we found a substantial negative impact on production output in the 3rd tertile group. In 2011, the total landed amount declined by approximately 90%. Although there was some recovery in the medium term, the long-run recovery was quite sluggish, and the total landed amounts remained more than 40% lower even after 10 years. The estimation results for sales show a similar tendency, although the magnitude of the negative impact was mitigated by an increase in price. Finally, we found that sales per fisher decreased by 20–30% in the mid and long terms. In summary, the damage from the disaster was severe and resulted in a persistent decline in productivity.

5.2 Heterogeneous Effects by Productivity

Estimation of productivity

The results suggest that the recovery of both capital and labor inputs and outputs has been limited despite the government's generous assistance. One key and interesting policy question is who reinvested capital in the fishing industry after the earthquake. In a competitive market, when an industry declines due to persistent negative productivity shocks, low-productivity firms tend to exit, whereas high-productivity firms survive. Consistent with this argument, Table 1 shows that per-capita sales increased substantially between 2000 and 2009 and between 2011 and 2020 for both treated and control prefectures (Columns 4 and 5). However, in the case of the Great East Japan Earthquake, the provision of generous government subsidies may have allowed low-productivity fishers to continue operating in the market. Therefore, this subsection investigates whether the impact of the earthquake is heterogeneous in terms of productivity.

Ideally, we would use fisher-level data to analyze heterogeneity by productivity. However, because we have only port-level data, our analysis relies on port-level productivity. We consider a simple Cobb-Douglas production function as follows:

$$Y_{ijt} = A_{ijt} K_{ijt}^{\beta_K} L_{ijt}^{\beta_L}, \tag{2}$$

where i, j, and t indicate port, prefecture, and year, respectively. Given that the port produces heterogeneous goods (i.e., different types of fish), we used sales instead of the landed amount as the production output Y_{ijt}.[6] We used the number of fishing boats registered at the port as capital input, K_{ijt}, and the number of fishers as labor input, L_{ijt}. We assumed that the total factor productivity is written as $A_{ijt} = exp\left(\alpha_i + x'_{ijt}\gamma + \phi_t + u_{ijt}\right)$, where x_{ijt} is a vector of observable port characteristics[7], ϕ_t is a year-specific shock, and u_{ijt} is the productivity shock that occurs after capital investment and labor input are determined; thus, we estimated port-level unobserved heterogeneity α_i as port fixed effects (FE). We estimated the log-transformed version of equation (2) as follows:

$$logY_{ijt} = \alpha_i + \beta_K logK_{ijt} + \beta_L LogL_{ijt} + x'_{ijt}\gamma + \phi_t + u_{ijt} \tag{3}$$

Because we need a large sample period to identify port FE, we use the sample between 1989 and 2009 to estimate equation (3).

Table A2 presents the estimation results for the production function with port FE. The estimated coefficients on the capital and labor inputs were 0.42 and 0.21, respectively, and thus, an additional boat contributes much more than an additional labor. The sum of these estimates is 0.63 and less than one, indicating decreasing returns to scale, which seems reasonable given the limited marine resources. We also estimated equation (3) by separately including the labor input by age category. While the estimated coefficient of capital remained almost unchanged, we found a positive association between sales and the number of young and elderly fishers, whereas no association was found between sales and the number of middle-aged fishers. Based on the port FE obtained from the estimation results in Column 1, we estimated port FE as the mean of the residual over 21 years and divided the ports into three groups based on the tertiles of port FE.[8]

[6] Since we used sales as output measure, market power to mark up the price is also included in "productivity."

[7] We used the category variables of the fishery port's facilities (unloading place, ice making, frozen, refrigerated, ice storage, and oil supply). For each facility, we constructed the category variable with zero for missing and zero values, one for 0-25 percentile, two for 25-50 percentile, three for 50-75 percentile, and four for 75-100 percentile. We also used fishery port type-year fixed effects and prefecture-year fixed effects.

[8] We demeaned the port FE for each prefecture to control for prefecture-level productivity.

Heterogeneous impact on production inputs

Figure 7 summarizes the estimation results of equation (1) for the production input by port-level productivity. Panel (a) shows that both high- and low-productivity ports lost approximately 60% of their boats due to the earthquake. However, the recovery was much faster in high-productivity ports. In 2016, the negative impact diminished to approximately 15% among high-productivity ports, while that among low-productivity ports remained at approximately 30%, although the low-productivity ports recovered to the same level as high-productivity ports in 2020. Note that the heterogeneity in the number of fishers is nuanced because of imprecise estimates for 2011 and 2013. However, no long-term heterogeneity was observed. The recovery in the capital equipment rate was similar to the recovery in the number of boats, and high-productivity ports recovered more quickly than low-productivity ports (Panel (c)). Finally, we found no substantial heterogeneity in the capital utilization rate (Panel (d)).

Our empirical evidence does not support the market-cleansing effect of such disasters. In our analysis, the disaster caused severe damage to both high- and low-productivity ports, and both groups recovered to similar levels in terms of production inputs in the long run. In particular, we did not find that the long-run negative impacts on the number of boats or fishers were larger in low-productivity ports than in high-productivity ones. This is probably because of generous government policies to reconstruct fishing ports and facilities, support fishing boat insurance payments, and subsidize fishing boats and equipment, where two-thirds of the cost of subsidized loans and the remaining one-third were covered by interest-free loans. As a result, a fisher with low productivity could survive in the market, even though they lost essential capital for fishing.

Heterogeneous impact on production outputs

Next, we move on to the heterogeneous impact on outputs (Figure 8). In terms of the landed amount, the initial impact of the earthquake was larger on low-productivity ports than on high-productivity ports. The latter recovered relatively quickly, by 2014, whereas the recovery of low-productivity ports was stagnant, until 2013. In both types of ports, the negative impacts on the landed amount remained non-negligible even five years after the earthquake. In the long run, the negative impact decreased to 0–20%for high-productivity ports, but remained at around 40–50% for low-productivity ones.

However, the long-term impact on sales shows a different pattern. For the high-productivity ports, the magnitude of the impact and pattern of recovery were comparable to those of the landed amount. By contrast, low-productivity ports experienced a 60–70% loss of sales between 2011 and 2013, their sales recovered up to -10% in 2015, and thereafter, the negative impact was no longer statistically different from zero. This difference between high- and low-productivity ports is mainly attributed to price changes(Panel (c)). While the price increased slightly among the high-productivity ports, the price increase among the low-productivity ports was substantial, at more than 50%, even in 2019. Since this increase in price outweighed the decrease in the landed amount, the negative impact on sales was alleviated among low-productivity ports.

The substantial increase in price could be explained, at least, by the demand-supply mechanism or composition change in terms of productivity or switching fishing types. First, price theory predicts that prices increase when supply decreases (holding demand constant). According to our data, fish from high-productivity ports are traded nationwide, including in the Tokyo fish market, whereas fish from low-productivity ports are mostly traded in the local fish market (Figure A7). As a result, the share of fish from highly productive ports in the market where they are traded would be smaller than that from low-productivity ports, and some fish from Tohoku region could be replaced by fish from other areas in large markets. Therefore, the demand-supply mechanism predicts that the price response is larger among low-productivity ports than among high-productivity ports.

Alternatively, the price change could reflect the change in the fish composition as we measure "price" as the sales per landed amount. Since the tsunami waves washed away fishing boats and capital for aquaculture, most fishers needed to renew this capital using government financial aid. Given that different types of fishing or aquaculture require different types of capital, this situation opened up an opportunity for them to switch types of fisheries, which would otherwise not be an affordable option due to large switching costs. Thus, it is possible that those who engaged in less profitable fishing methods before the earthquake switched to more profitable fishing methods, thus changing the fish composition.

To examine whether the price change was driven by changes in fish composition, we re-estimated the effect of the earthquake on price by controlling for fish composition. In particular, because we observe the landed amount for each type of fish $Fish_k$ at each port, we estimate the following:

$$y_{ijt} = \beta DID_{jt} + x'_{jt}\gamma + \sum_k \delta_k Fish_{kit} + \theta_i + \eta_t + u_{ijt},$$

where we used port-level information for this analysis, and i indicates each port. The dependent variable is the logged price, x includes the same set of control variables as in equation (1), and DID_{jt} takes one for Miyagi or Iwate and after 2011.

Columns 1 and 3 of Table 2 show the estimation results without controlling for fish composition, reassuring us that the price increase was larger in low-productivity ports than in high-productivity ports. Columns 2 and 4 show the estimation results after controlling for fish composition. We found substantial differences between these two groups. In low-productivity ports, the effect on price was unchanged, or if any, became larger when fish composition was controlled, indicating that this price increase was not explained by fish composition at all. Thus, their price increases would be driven by the demand-supply mechanism, as discussed earlier. However, the positive impact on price diminished in highly productive ports once fish composition was controlled. This suggests that they substantially changed fish types and/or fishing methods after the earthquake, presumably because of lowered switching costs due to tsunami damage and government financial aid. In the next subsection, we further discuss how fishers switched fishing technologies.

There are several concerns about the estimation of production functions. First, our model does not include material inputs owing to limitations in data availability. Specifically, the amount of material input may depend on fishing techniques. To partially address this issue, we re-estimate the production function by controlling for the composition of fishing techniques. We find that the results of our analysis of heterogeneity by port productivity, as discussed above, remain virtually unchanged with this specification (Figures A8–A11). Second, it is possible that large ports have rich fishing infrastructure that was not captured in the data, leading to the misclassification of these ports as highly productive. To address this, we repeat our analysis by excluding large ports, specifically type 3 ports, from the analysis sample.[9] Our estimation results are almost identical to those of our baseline specification (Figures A12–A15). Therefore, we confirm that our results are not driven by large ports with rich fishing infrastructure.

5.3 Switching fishing technology

In the previous subsection, we found that fish composition was affected by the disaster, particularly in highly productive ports. There are at least two possible explanations for this observation. First, the tsunami washed away not only mariculture equipment, but also (shellfish) fry. As it takes time for new fry to mature, this direct damage can mechanically alter the fish composition. Second, the loss of legacy capital and the availability of generous government subsidies created opportunities to upgrade fishing equipment and potentially adopt new fishing methods. To distinguish between these mechanisms, we separately analyzed newly adopted fishing methods and fishing methods

[9] For Type 3 fishing ports, it is generally required to meet at least three of the following criteria: (a) The number of local fishing vessels is 140 or more (98 or more for fishing ports along the Sea of Japan), or the total tonnage of those vessels is 2,400 tons or more (1,680 tons or more for fishing ports along the Sea of Japan). (b) The number of fishing vessels using the port is 70 or more (49 or more for fishing ports along the Sea of Japan), or the total tonnage of those vessels is 1,600 tons or more (1,120 tons or more for fishing ports along the Sea of Japan), and there is usage by fishing vessels from multiple prefectures. (c) The annual landing volume of local catches is 5,000 tons or more (3,500 tons or more for fishing ports along the Sea of Japan). (d) The port has all of the following facilities: (i) Mooring facilities; (ii) A port road or port railway with a width of 5.5 meters or more; (iii) A handling facility; (iv) A fishing vessel repair yard; (v) A water supply facility; (vi) A fuel supply facility; (vii) An ice-making facility: (viii) A freezing facility; (ix) A refrigeration facility.

discontinued.

In our data, each port report the amount landed using fishing methods. There are four major categories for fishing (netting, angling, whaling, and others) and four major categories for mariculture (fish, shellfish, seaweed, and others), with 57 subcategories based on location of fishing, scale of net, and type of fish. Because these data are available from 2005, we divided our sample period into 2005–2009, 2011–2016, and 2017–2020. We then defined a new method as a fishing method with zero landed amounts between 2005 and 2009, but with a positive landed amount between 2011 and 2016 or 2017 and 2020. Similarly, we defined the discontinued method as fishing methods with a positive landed amount between 2005 and 2009 but with zero landed amount between 2011 and 2016 or 2017 and 2020. Then, we estimated the following equation using port-level data:

$$y_i = \beta_0 + \beta_1 D_i + u_i,$$

where the dependent variables are the number of new methods and the number of discontinued methods in each period. Note that because the dependent variables are differences in fishing methods before and after the earthquake, this estimation equation is regarded as a port-level first-difference model; thus, port-level time-invariant heterogeneity is already partialled out.

Table 3 shows the substantial heterogeneity in port-level productivity. Low-productivity ports did not adopt new fishing methods in both post-disaster periods, while high-productivity ports adopted 0.8–1.4 new method on average (Columns 1 and 3). The size of the change is notable, considering that the pre-disaster average number of fishing methods was 15.5, translating to an increase of 5.5 to 8.7%. Columns 2 and 4 indicate that the number of discontinued methods also increased in both the mid- and long-term. While this increase was expected, given the severe damage to fishing and mariculture equipment, we observed that the persistence of this impact varied with productivity. If the effect stemmed from direct damage, we would anticipate it to diminish over time as fishers replace their boats and fishing equipment. Indeed, the effect size decreased to 62% (= 1.119/1.815) in low-productivity ports across the two post-disaster periods. By contrast, the effect remained persistent in highly productive ports, with 78% (= 1.999/2.578) of the initial impact remaining. This also suggests that fishers in highly productive ports switch from one fishing method to another, leading to a persistent increase in the number of discontinued methods.

To summarize, we found that productive fishers tended to adopt new fishing technologies after the earthquake, whereas low-productivity fishers did not. Considering that we did not find substantial heterogeneity in the recovery of the number of boats in the long run, low-productivity fishers would simply renew or upgrade their legacy capital but would not attempt to switch to potentially more productive fishers. Although access to capital is essential for quick recovery from disasters (De Mel et al., 2012), providing unconditional subsidies would not be efficient from an economic viewpoint because it could be used by low-productivity firms to survive. While the literature does not agree on the market cleansing or creative destruction effect of disasters, our analysis underlines the importance of policies to recover from disasters, as productive firms utilize subsidies differently from unproductive firms.

6 Conclusion

This study analyzed the impact of the Great East Japan Earthquake on the fishing industry in Iwate and Miyagi prefectures, focusing on its impact on production inputs and outputs. The results show that the earthquake and tsunami waves washed away approximately 60% of the fishing boats, and sales decreased by 60% in the year of the disaster. Despite generous subsidies from the government, non-negligible negative impacts remained, even 10 years after the earthquake. In response to the supply shortage of fish from Tohoku region, prices increased substantially and persistently. Although some previous studies have pointed out the market-cleansing effect of disasters, our heterogeneity analysis by productivity did not show that fishers in low-productivity ports were more likely to exit the market than those in highly productive ports, which seems to be owing to the generous government financial aid for the reconstruction of fishing ports and re-investment in fishing capital. However, we found evidence that fishers, particularly those at highly productive ports, adopted new fishing methods, suggesting that disasters could facilitate technology switching, a form of creative destruction.

References

Abadie, Alberto, Alexis Diamond, and Jens Hainmueller, "Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program," *Journal of the American Statistical Association*, 2010, *105* (490), 493–505.

Akesaka, Mika, "Change in time preferences: Evidence from the Great East Japan Earthquake," *Journal of Economic Behavior & Organization*, 2019, *166*, 239–245.

Barone, Guglielmo and Sauro Mocetti, "Natural disasters, growth and institutions: A tale of two earthquakes," *Journal of Urban Economics*, 2014, *84*, 52–66.

Belasen, Ariel R. and Solomon W. Polachek, "How Disasters Affect Local Labor Markets: The Effects of Hurricanes in Florida," *The Journal of Human Resources*, 2009, *44* (1), 251–276.

Boustan, Leah Platt, Matthew E. Kahn, and Paul W. Rhode, "Moving to Higher Ground: Migration Response to Natural Disasters in the Early Twentieth Century," *American Economic Review*, May 2012, *102* (3), 238–244.

_ , Matthew E Kahn, Paul W Rhode, and Maria Lucia Yanguas, "The Effect of Natural Disasters on Economic Activity in US Counties: A Century of Data," Working Paper 23410, National Bureau of Economic Research May 2019.

Caruso, German Daniel, "The legacy of natural disasters: The intergenerational impact of 100 years of disasters in Latin America," *Journal of Development Economics*, 2017, *127*, 209 – 233.

Carvalho, Vasco M., Makoto Nirei, Yukiko U. Saito, and Alireza Tahbaz-Salehi, "Supply Chain Disruptions: Evidence from the Great East Japan Earthquake," Discussion Paper 16A-15, Policy Research Institute, Ministry of Finance 2016.

Cavallo, Alberto, Eduardo Cavallo, and Roberto Rigobon, "Prices and Supply Disruptions during Natural Disasters," *Review of Income and Wealth*, 2014, *60* (S2), S449–S471.

Cavallo, Eduardo, Sebastian Galiani, Ilan Noy, and Juan Pantano, "Catastrophic Natural Disasters and Economic Growth," *The Review of Economics and Statistics*, 2013, *95* (5), 1549–1561.

Cole, Matthew A, Robert J R Elliott, Toshihiro Okubo, and Eric Strobl, "Natural disasters and spatial heterogeneity in damages: the birth, life and death of manufacturing plants," *Journal of Economic Geography*, 11 2019, *19* (2), 373–408.

Cuaresma, Jesus Crespo, "Natural Disasters and Human Capital Accumulation," *World Bank Economic Review*, 2010, *24* (2), 280–302.

Deryugina, Tatyana, Laura Kawano, and Steven Levitt, "The Economic Impact of Hurricane Katrina on Its Victims: Evidence from Individual Tax Returns," *American Economic Journal: Applied Economics*, April 2018, *10* (2), 202–33.

Felbermayr, Gabriel and Jasmin Groschl, "Naturally negative: The growth effects of natural disasters," *Journal of Development Economics*, 2014, *111*, 92 – 106. Special Issue: Imbalances in Economic Development.

Gagnon, Etienne and David Lopez-Salido, "Small Price Responses to Large Demand Shocks," *Journal of the European Economic Association*, 02 2019, *18* (2), 792–828.

Genda, Yuji, "The effect of the Great East Japan Earthquake on employment (*Higashi-nihon dai-shinsai ga shigoto ni ataeta eikyo*)," *The Japanese Journal of Labour Studies*, 2014, *653*, 100–120. (in Japanese).

Groen, Jeffrey A. and Anne E. Polivka, "The Effect of Hurricane Katrina on the Labor Market Outcomes of Evacuees," *American Economic Review*, May 2008, *98* (2), 43–48.

Hanaoka, Chie, Hitoshi Shigeoka, and Yasutora Watanabe, "Do Risk Preferences Change? Evidence from the Great East Japan Earthquake," *American Economic Journal: Applied Economics*, April 2018, *10* (2), 298–330.

Higuchi, Yoshio, Tomohiko Inui, Toshiaki Hosoi, Isao Tanabe, and Aatsushi Kawakami, "The Impact of the Great East Japan Earthquake on the Labor Market—Need to Resolve the Employment Mismatch in the Disaster-Stricken Areas," *Japan Labor Review*, 2012, *9* (4), 4–21.

Hornbeck, Richard and Daniel Keniston, "Creative Destruction: Barriers to Urban Growth and the Great Boston Fire of 1872," *American Economic Review*, June 2017, *107* (6), 1365–98.

Hosono, Kaoru, Daisuke Miyakawa, Taisuke Uchino, Makoto Hazama, Arito Ono, Hirofumi Uchida, and Iichiro Uesugi, "Natural Disasters, Damage to Banks, and Firm Investment," *International Economic Review*, 2016, *57* (4), 1335–1370.

Hsiang, Solomon M and Amir S Jina, "The Causal Effect of Environmental Catastrophe on Long-Run Economic Growth: Evidence From 6,700 Cyclones," Working Paper 20352, National Bureau of Economic Research July 2014.

Imberman, Scott A., Adriana D. Kugler, and Bruce I. Sacerdote, "Katrina's Children: Evidence on the Structure of Peer Effects from Hurricane Evacuees," *American Economic Review*, May 2012, *102* (5), 2048–82.

Kawaguchi, Daiji and Norifumi Yukutake, "Estimating the residential land damage of the Fukushima nuclear accident," *Journal of Urban Economics*, 2017, *99*, 148 – 160.

Kondo, Ayako, "The effects of supply chain disruptions caused by the Great East Japan Earthquake on workers," *Japan and the World Economy*, 2018, *47*, 40–50.

Loayza, Norman V., Eduardo Olaberria, Jamele Rigolini, and Luc Christiaensen, "Natural Disasters and Growth: Going Beyond the Averages," *World Development*, 2012, *40* (7), 1317–1336.

McIntosh, Molly Fifer, "Measuring the Labor Market Impacts of Hurricane Katrina Migration: Evidence from Houston, Texas," *American Economic Review*, May 2008, *98* (2), 54–57.

Mel, Suresh De, David McKenzie, and Christopher Woodruff, "Enterprise Recovery Following Natural Disasters," *The Economic Journal*, 2012, *122* (559), 64–91.

Noth, Felix and Oliver Rehbein, "Badly hurt? Natural disasters and direct firm effects," *Finance Research Letters*, 2019, *28*, 254 – 258.

Noy, Ilan, "The macroeconomic consequences of disasters," *Journal of Development Economics*, 2009, *88* (2), 221 – 231.

Okazaki, Tetsuji, Toshihiro Okubo, and Eric Strobl, "Creative Destruction of Industries: Yokohama City in the Great Kanto Earthquake, 1923," *The Journal of Economic History*, 2019, *79* (1), 131.

Skidmore, Mark and Hideki Toya, "Do Natural Disasters Promote Long-Run Growth?," *Economic Inquiry*, 2002, *40* (4), 664–687.

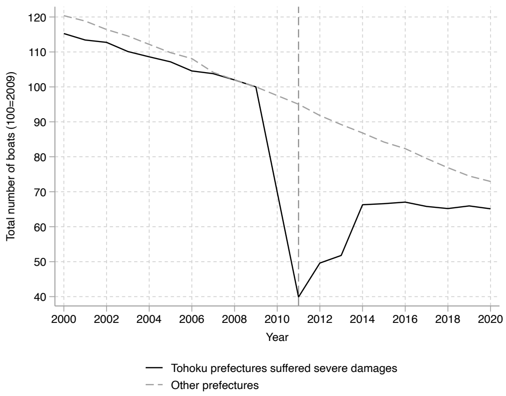
Strömberg, David, "Natural Disasters, Economic Development, and Humanitarian Aid," *Journal of Economic Perspectives*, September 2007, *21* (3), 199–222.

Sugano, Saki, "The Well-Being of Elderly Survivors after Natural Disasters: Measuring the Impact of the Great East Japan Earthquake," *The Japanese Economic Review*, 2016, *67* (2), 211–229.

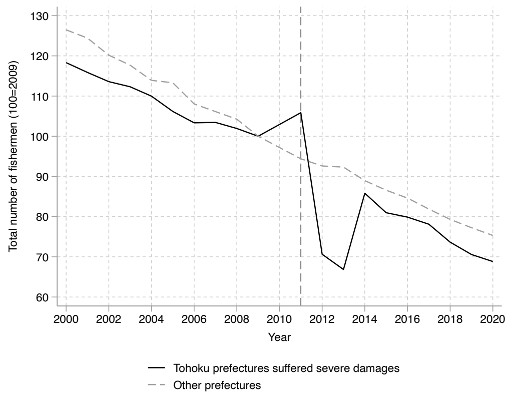
Tajima, Kayo, Masashi Yamamoto, and Daisuke Ichinose, "How do agricultural markets respond to radiation risk? Evidence from the 2011 disaster in Japan," *Regional Science and Urban Economics*, 2016, *60*, 20 – 30.

Tanaka, Ayumu, "The impacts of natural disasters on plants' growth: Evidence from the Great Hanshin-Awaji (Kobe) earthquake," *Regional Science and Urban Economics*, 2015, *50*, 31 – 41.

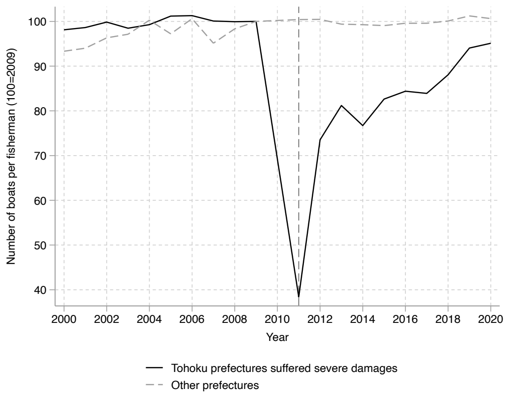
Yamasaki, Izumi, Miho Takizawa, Tomohiko Inui, Rubkwan Thurmanpornphilasd, Yoshio Higuchi, and Makiko Nakamuro, "Labor Market Outcomes of the Evacuees of the Great East Japan Earthquake," Working Paper, Economic and Social Research Institute, Cabinet Office 2016.



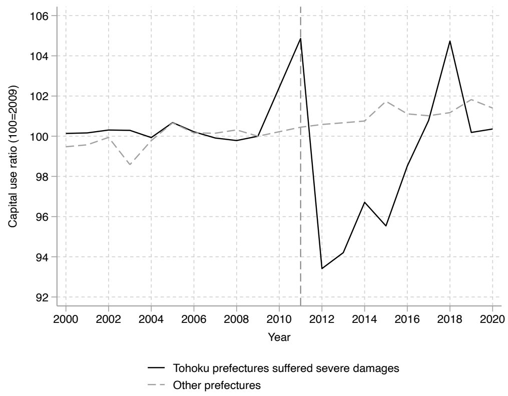
(a) Number of boats



(b) Number of fishers



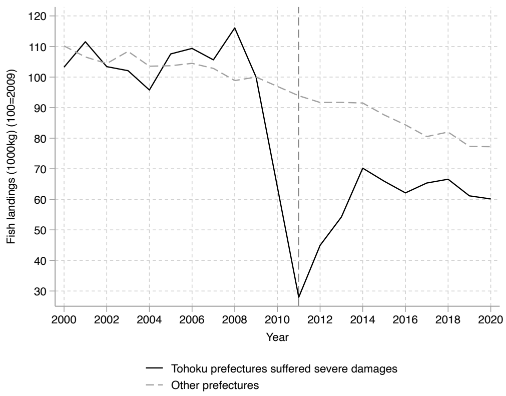
(c) Capital equipment rate (Boats per fisher)



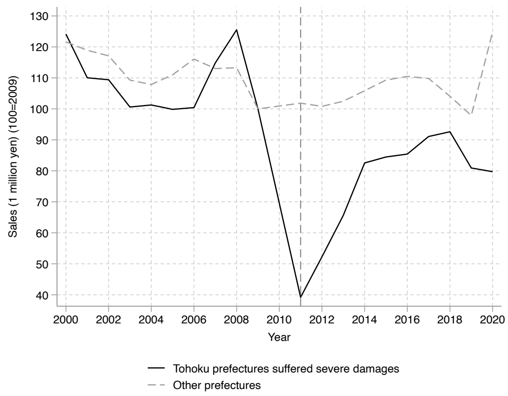
(d) Capital utilization ratio

Figure 1: Trends in average number of boats and fishers

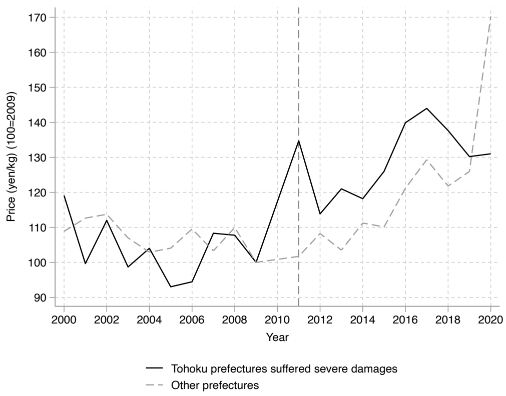
Note: The figures represent the average values of the prefecture-level variables. We used all types of fish ports except those located on remote islands. The label "Tohoku prefectures suffered severe damages" represents Iwate and Miyagi. The label "Other prefectures" represents all other prefectures except for the aforementioned three.



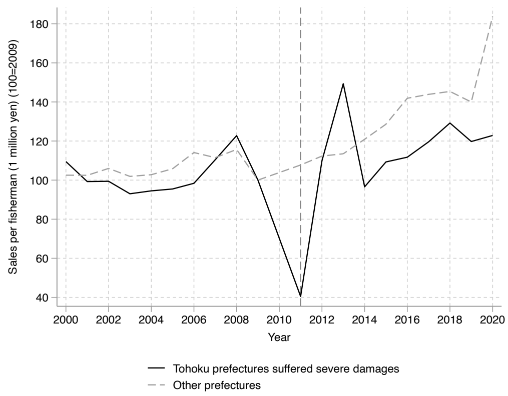
(a) Total landed amount (1000kg)



(b) Sales (1 million JPY)



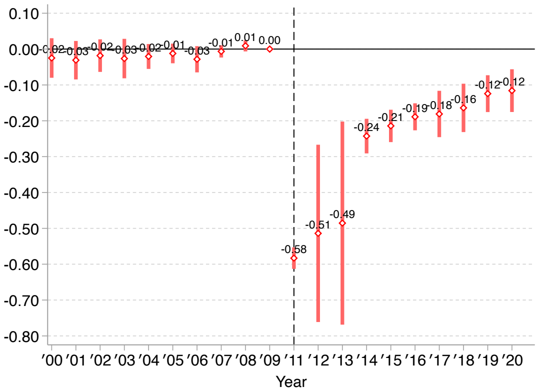
(c) Average price (1 JPY/kg)



(d) Sales per fisher (1 million JPY)

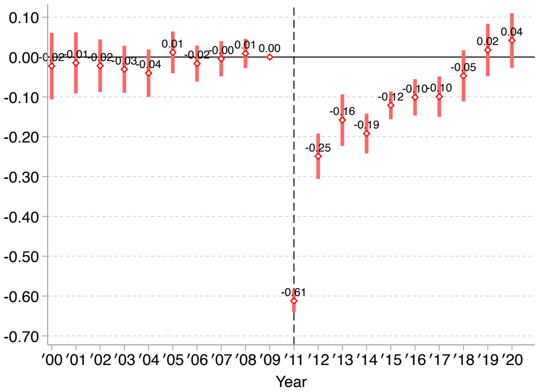
Figure 2: Trends in total landed amounts, sales and price

Note: The figures represent the average values of the prefecture-level variables (Panels (a) and (b)). Panel (c) represents the average value of the price index (the prefecture-level sales volume/the prefecture-level landed amount), and Panel (d) represents that of the landed amount per fisher (the prefecture-level sales volume/the prefecture-level number of total fishers). We used all types of fish ports except those located on remote islands. The label “Tohoku prefectures suffered severe damages” represents Iwate and Miyagi. The label “Other prefectures” represents all other prefectures except for the aforementioned three.



(a) Number of boats

(b) Number of fishers

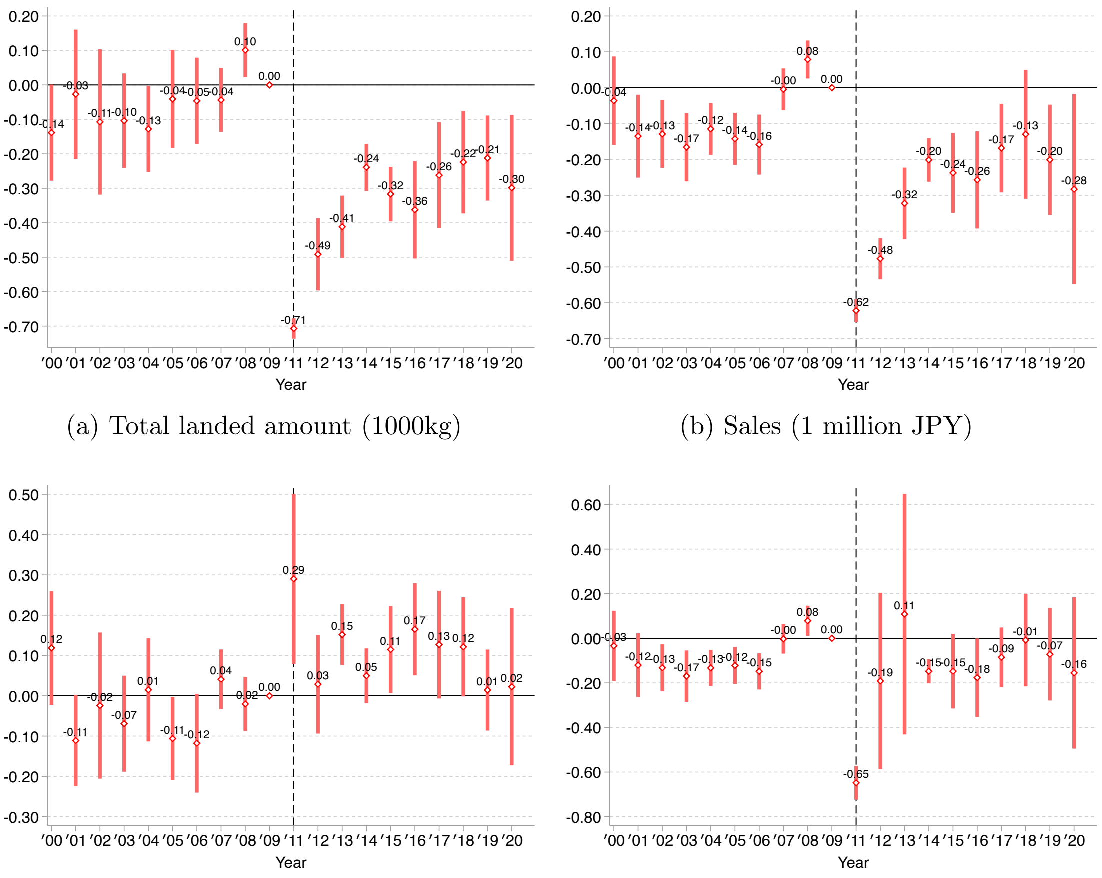


(c) Capital equipment rate (Boats per fisher)

(d) Capital utilization ratio

Figure 3: Effects of the disaster on production inputs

Note: We used all types of fish ports except those located on remote islands. The dependent variables were log-translated. The markers indicate $\exp\left(\hat{\beta}_j\right) - 1$ for the year j, where $\hat{\beta}_j$ are the estimates of the cross term of the treatment dummy and the year dummy variables, and the bars are the 95% confidence intervals for the estimates. The confidence intervals were calculated using standard errors robust against prefecture-level clustering (39 prefectures).



(a) Total landed amount (1000kg)

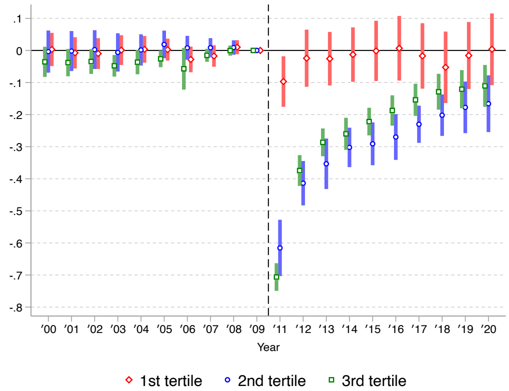
(b) Sales (1 million JPY)

(c) Average price (1 JPY/kg)

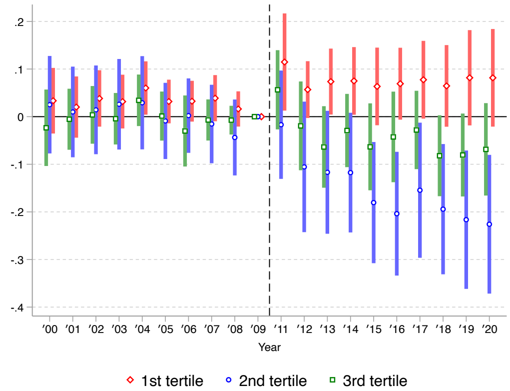
(d) Sales per fisher (1 million JPY)

Figure 4: Effects of the disaster on production outputs

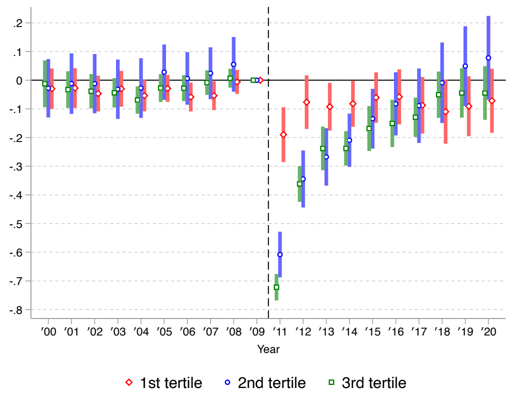
Note: We used all types of fish ports except those located on remote islands. The dependent variables were log-translated. The markers indicate $\exp\left(\hat{\beta}_j\right) - 1$ for the year j, where $\hat{\beta}_j$ are the estimates of the cross term of the treatment dummy and the year dummy variables, and the bars are the 95% confidence intervals for the estimates. The confidence intervals were calculated using standard errors robust against prefecture-level clustering (39 prefectures).



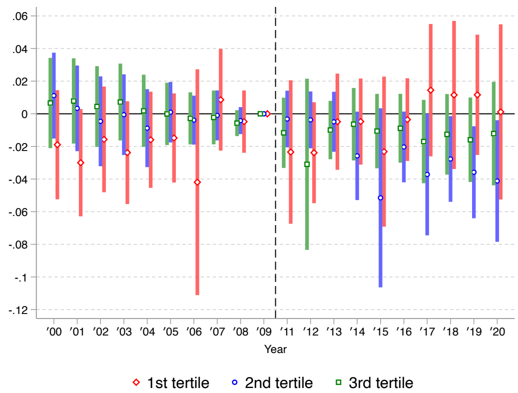
(a) Number of boats



(b) Number of fishers



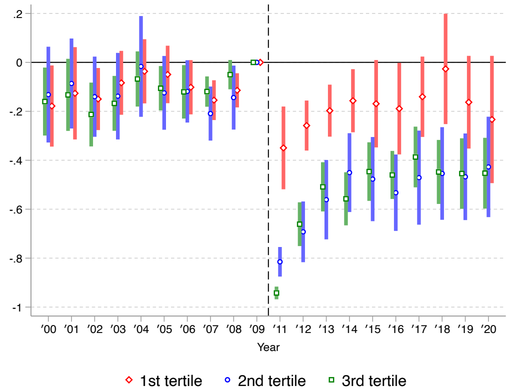
(c) Capital equipment rate (Boats per fisher)



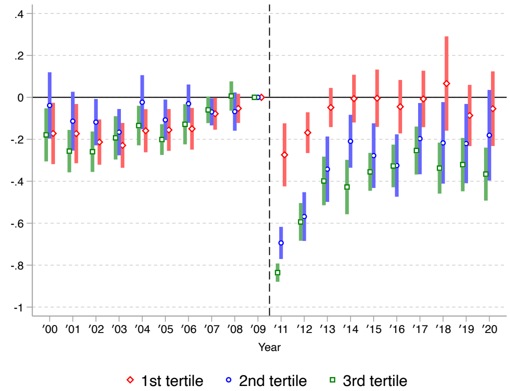
(d) Capital utilization ratio

Figure 5: Effects of the disaster on production inputs by the severity of tsunami

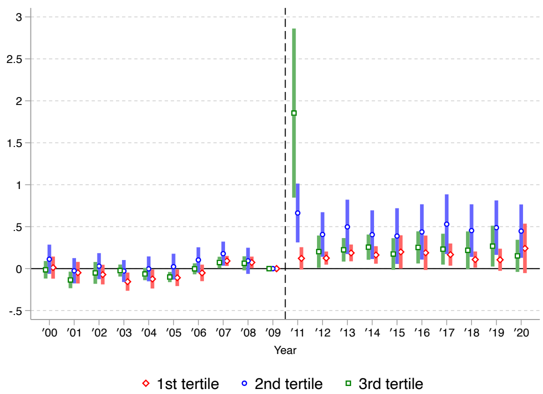
Note: The unit of observation is port and year. We used all types of fish ports except those located on remote islands. The dependent variables are log-translated. In the estimation, the total number of fishers in 2009 for each port was used as a weight. The markers indicate $\exp\left(\hat{\beta}_j\right) - 1$ for the year j, where $\hat{\beta}_j$ are the estimates of the cross term of the treatment dummy and the year dummy variables, and the bars are the 95% confidence intervals for the estimates. The confidence intervals were calculated using standard errors robust against port-level clustering. The tsunami height variable was categorized into four levels: zero, first tertile, second tertile, and third tertile. Ports without matching tsunami height data were assigned a tsunami height of zero. Tertiles were calculated based on data excluding ports with a tsunami height of zero.



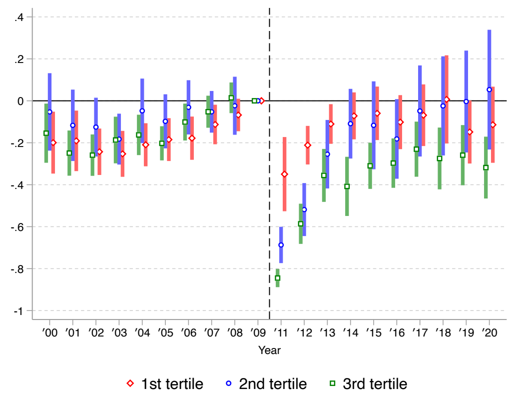
(a) Total landed amount (1000kg)



(b) Sales (1 million JPY)



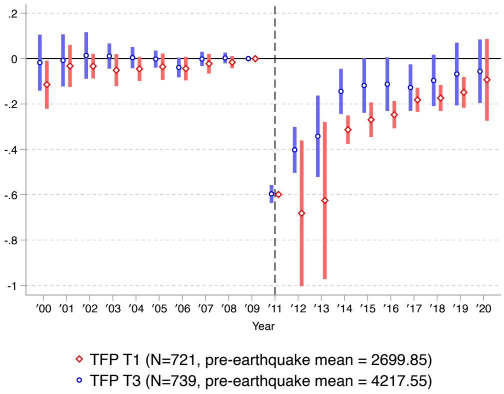
(c) Average price (1 JPY/kg)



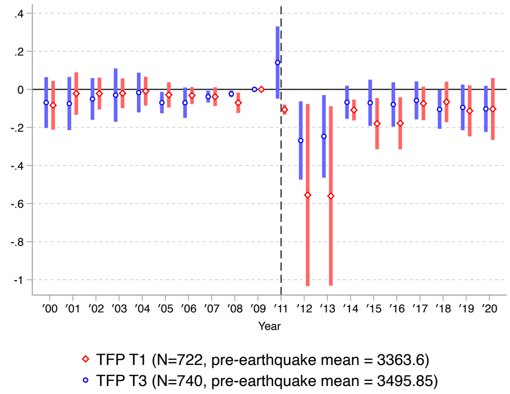
(d) Sales per fisher (1 million JPY)

Figure 6: Effects of the disaster on production outputs by the severity of tsunami

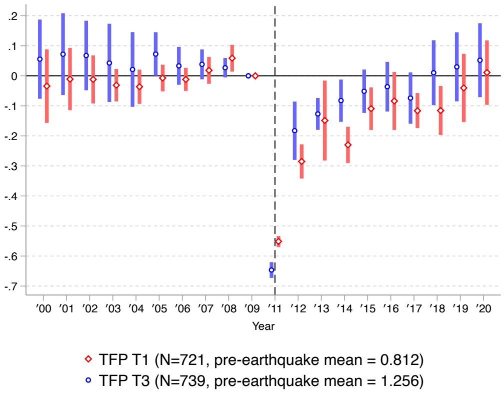
Note: The unit of observation is port and year. We used all types of fish ports except those located on remote islands. The dependent variables were log-translated. In the estimation, the total number of fishers in 2009 for each port was used as a weight. The markers indicate $\exp\left(\hat{\beta}_j\right) - 1$ for the year j, where $\hat{\beta}_j$ are the estimates of the cross term of the treatment dummy and the year dummy variables, and the bars are the 95% confidence intervals for the estimates. The confidence intervals were calculated using standard errors robust against port-level clustering. The tsunami height variable was categorized into four levels: zero, first tertile, second tertile, and third tertile. Ports without matching tsunami height data were assigned a tsunami height of zero. Tertiles were calculated based on data excluding ports with a tsunami height of zero.



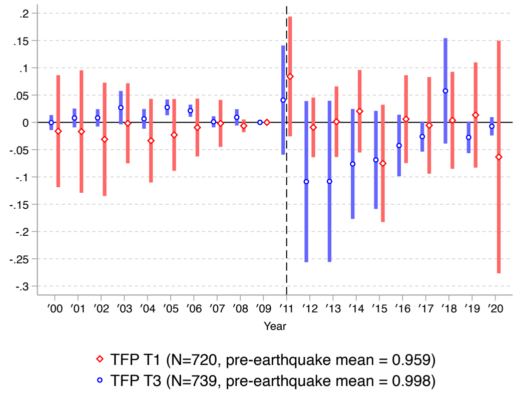
(a) Number of boats



(b) Number of fishers



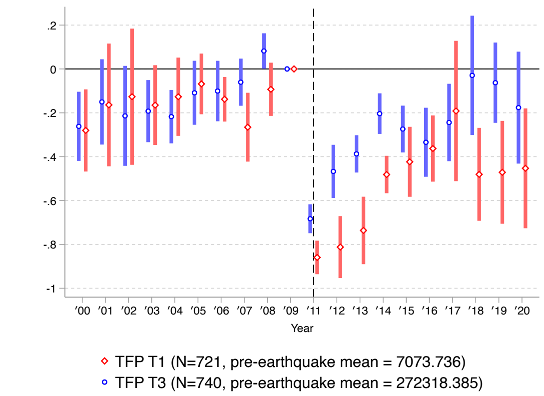
(c) Capital equipment rate (Boats per fisher)



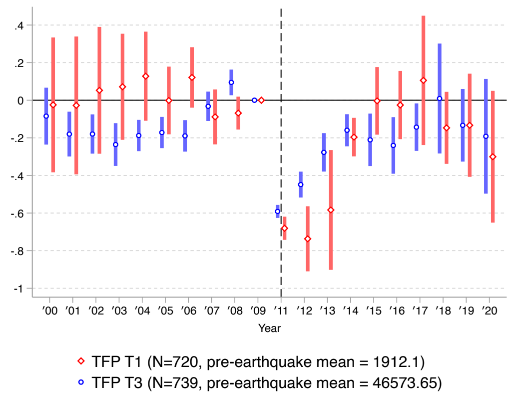
(d) Capital utilization ratio

Figure 7: Effects of the disaster by port-level TFP on inputs: T1 versus T3

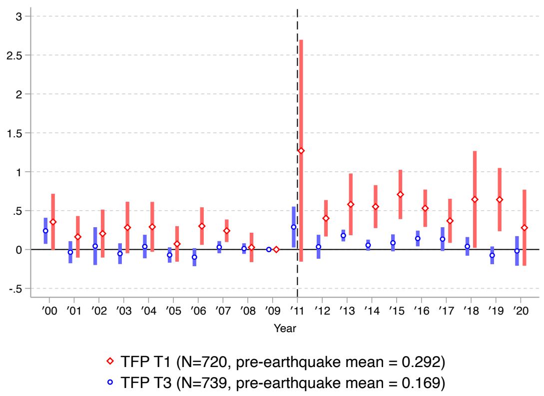
Note: We used all types of fish ports except those located on remote islands. The dependent variables were log-translated. The markers indicate $\exp\left(\hat{\beta}_j\right) - 1$ for the year j, where $\hat{\beta}_j$ are the estimates of the cross term of the treatment dummy and the year dummy variables, and the bars are the 95% confidence intervals for the estimates. The confidence intervals were calculated using standard errors robust against prefecture-level clustering (39 prefectures).



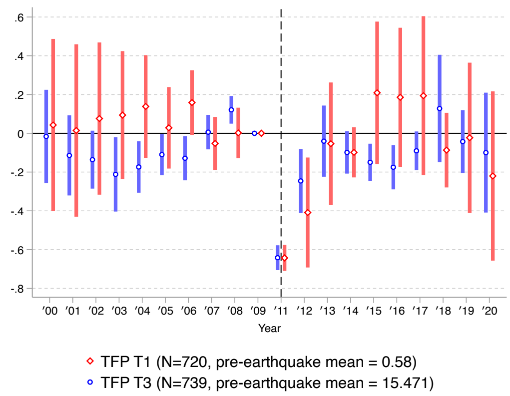
(a) Total landed amount (1000kg)



(b) Sales (1 million JPY)



(c) Average price (1 JPY/kg)



(d) Sales per fisher (1 million JPY)

Figure 8: Effects of the disaster by port-level TFP on outputs: T1 versus T3

Note: We used all types of fish ports except those located on remote islands. The dependent variables were log-translated. The markers indicate $\exp\left(\hat{\beta}_j\right) - 1$ for the year j, where $\hat{\beta}_j$ are the estimates of the cross term of the treatment dummy and the year dummy variables, and the bars are the 95% confidence intervals for the estimates. The confidence intervals were calculated using standard errors robust against prefecture-level clustering (39 prefectures).

Table 1: Summary Statistics

		Iwate and Miyagi		Others	
	(1) Whole	(2) Pre	(3) Post	(4) Pre	(5) Post
Total number of boats	4401.54	12917.25	7231.25	4661.69	3511.10
less than 3,000kg (%)	0.68	0.88	0.87	0.67	0.66
3,000 -5,000kg (%)	0.19	0.06	0.06	0.20	0.19
5,000 - 10,000kg (%)	0.08	0.03	0.03	0.08	0.09
more than 10,000kg (%)	0.05	0.03	0.03	0.05	0.06
Number of fishers	6020.00	12044.10	8672.15	6596.43	4961.56
Number of boats per fisher	0.79	1.09	0.87	0.76	0.79
Capital utilization rate	0.97	0.99	0.98	0.96	0.98
Total landed amount					
1000kg	95264.37	320117.53	175596.73	95242.28	78331.72
1 million JPY	25987.54	57950.65	40225.95	25387.70	24020.63
JPY per kg	390.86	182.94	228.72	377.98	424.31
1 million JPY per fisher	4.63	5.48	5.94	4.05	5.09
Number of observations	760	20	20	360	360
Number of prefectures	38	2	2	36	36
Number of ports	2451	245	245	2206	2206

The unit of observation is prefecture-year. The average values are reported. We used the data from 2000 to 2020.

Table 2: Effects of disaster on price conditional on fish composition

	TFP=T1		TFP=T3	
	(1)	(2)	(3)	(4)
DID	0.384^{**}	0.413^{***}	0.175^{*}	0.0777
	(0.161)	(0.0719)	(0.0972)	(0.0584)
Number of observations	5821	5821	6579	6579
Landed amount by each fish		X		X

The unit of observation is port-year. We used all types of fish ports except those located on remote islands for the prefecture-level aggregation. The dependent variables are logged prices. All models also include the region-specific linear trends, the port fixed effects, prefecture fixed effects, and year fixed effects. Columns (2) and (4) also include the landed amount by each fish. "DID" indicates $\exp\left(\hat{\beta}_{DID}\right) - 1$, where $\hat{\beta}_{DID}$ is the DID estimate. Standard errors robust against prefecture-level clustering are shown between parentheses. Statistical significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3: Change in Fishing Methods

	2011-2015		2016-2020	
	(1)	(2)	(3)	(4)
	N new	N stop	N new	N stop
A. Low productive ports				
Treat	0.142	1.815***	0.304	1.119***
	(0.355)	(0.481)	(0.324)	(0.406)
Number of observations	451	451	451	451
Pre-earthquake mean (Treated)	8.1	8.1	8.1	8.1
B. High productive ports				
Treat	0.846**	2.578***	1.357*	1.999***
	(0.411)	(0.293)	(0.690)	(0.548)
Number of observations	459	459	459	459
Pre-earthquake mean (Treated)	15.5	15.5	15.5	15.5

The unit of observation is the port. The dependent variables are the number of new fishing methods that fishers adopted and the number of fishing methods that fishers discontinued between the pre-earthquake period (2005-2009) and the post-earthquake periods (2011-2015 for Columns (1) and (2), and 2016-2020 for Columns (3) and (4)). We regressed the dependent variables on the dummy variable indicating whether the Tohoku prefectures suffered severe damage using weighted least squares, where the total number of fishers in 2009 for each port was used as a weight. Standard errors robust against clustering at the prefecture level are indicated in parentheses. Inference: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A Supplementary figures and tables

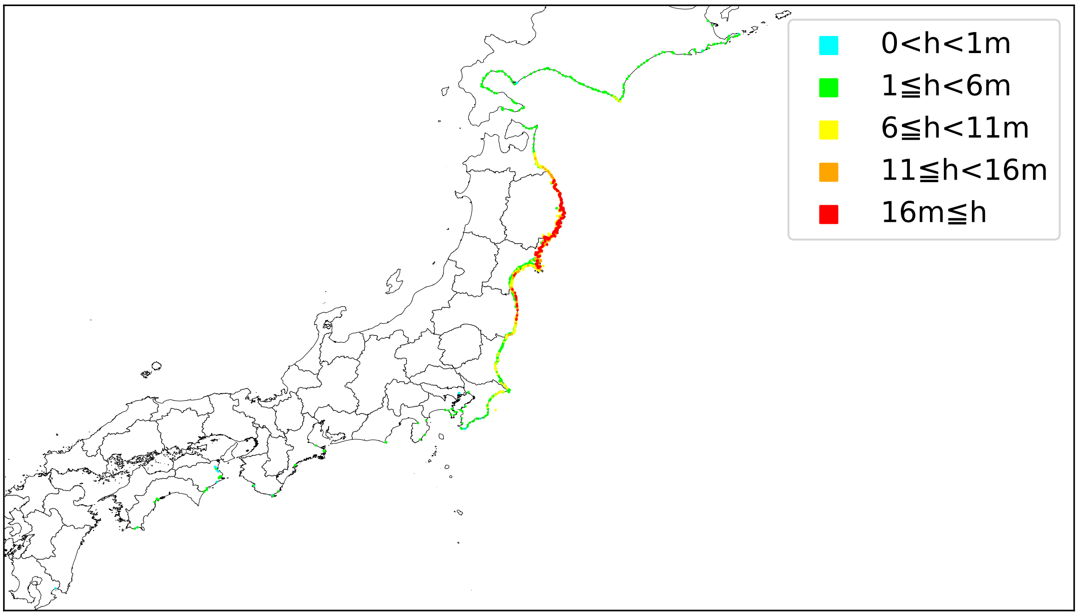
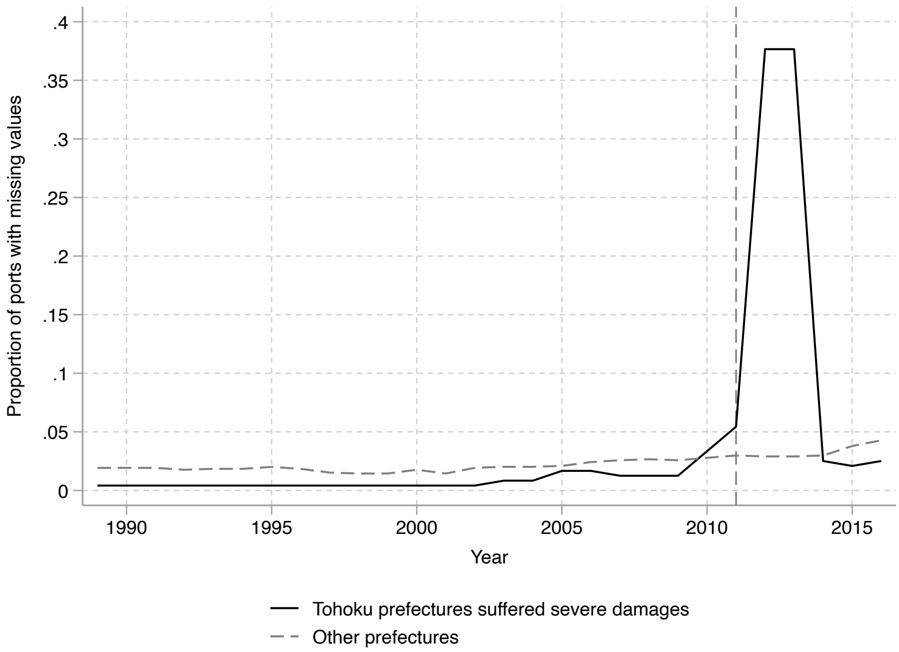
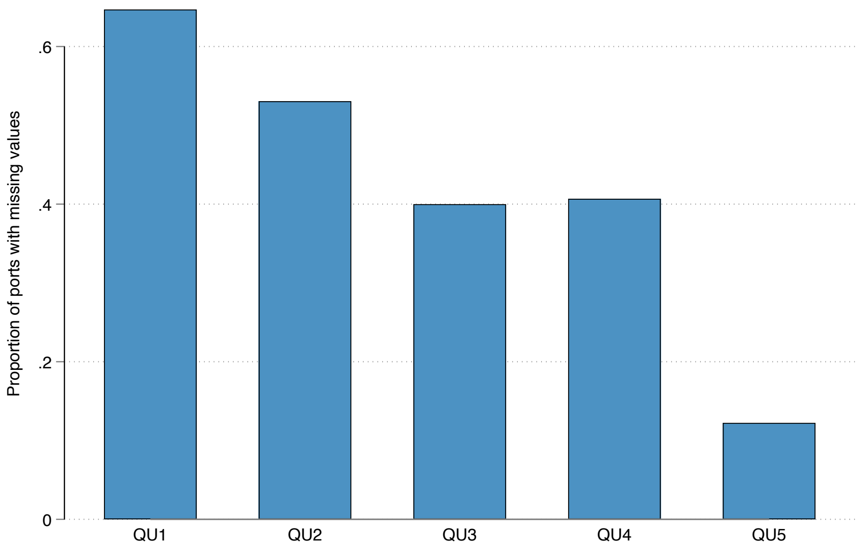


Figure A1: Geographical distribution of tsunami waves

Source: The 2011 Tohoku Earthquake Tsunami Joint Survey (TTJS) Group.



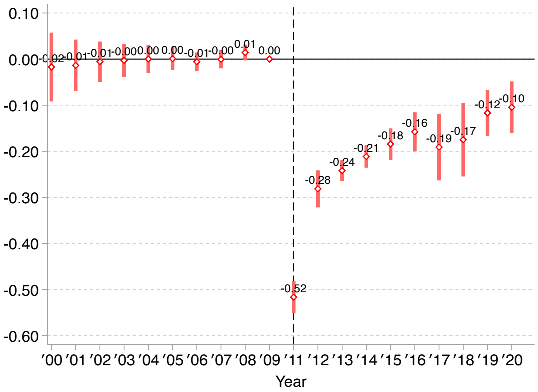
(a) By year



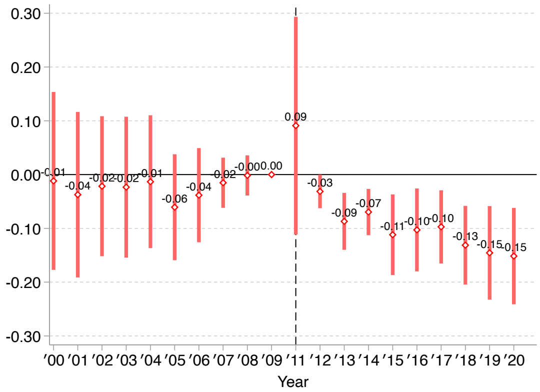
(b) By port size in 2009 (Tohoku prefectures suffered severe damages) (2011-2013)

Figure A2: Proportion of ports with missing values

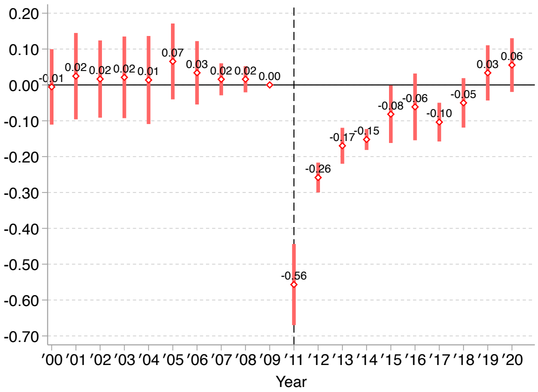
Note: The vertical line represents the proportion of ports with missing fishers numbers. In Panel (b), we computed the proportion of ports with missing values at least once between 2011 and 2013. Additionally, we calculated the proportion by quintiles of the number of fishers in 2009.



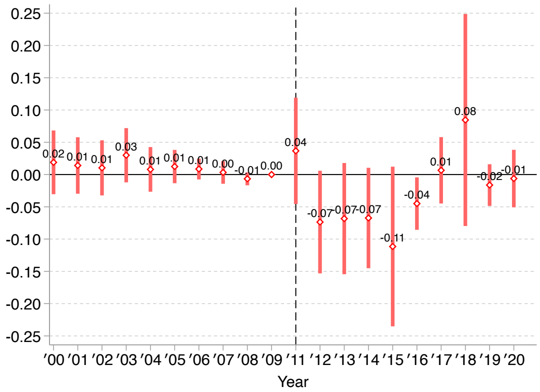
(a) Number of boats



(b) Number of fishers



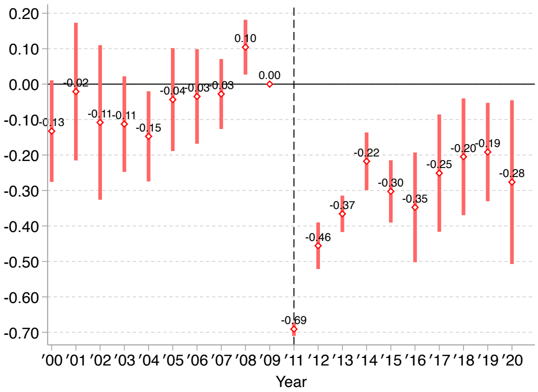
(c) Capital equipment rate (Boats per fisher)



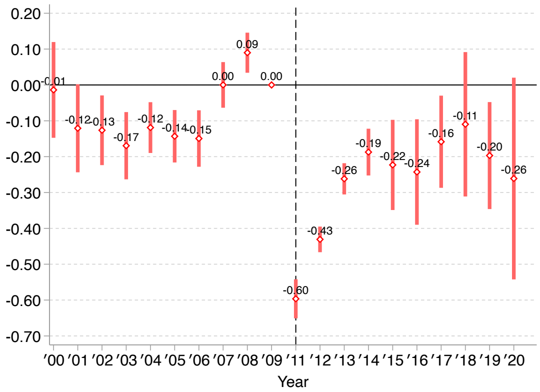
(d) Capital utilization ratio

Figure A3: Effects of the disaster on production inputs (excluding ports not participating in the survey (2011–2013))

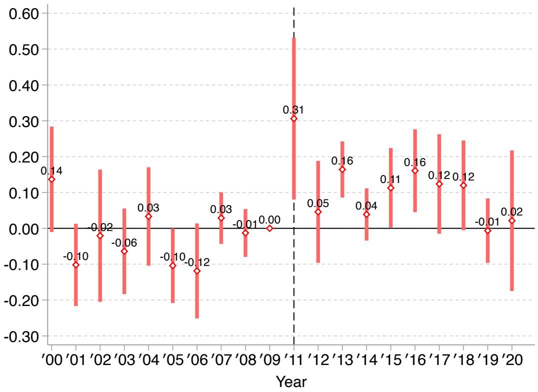
Note: We used all types of fish ports, except those located on remote islands, to create the figures. We also excluded ports that did not participate in the Topography of Fishery Ports survey at least once between 2011 and 2013. The dependent variables are log-translated. The markers indicate $\exp\left(\hat{\beta}_j\right) - 1$ for the year j, where $\hat{\beta}_j$ are the estimates of the cross term of the treatment dummy and the year dummy variables, and the bars are the 95 % confidence intervals for the estimates. The confidence intervals are calculated using standard errors robust against prefecture-level clustering (39 prefectures).



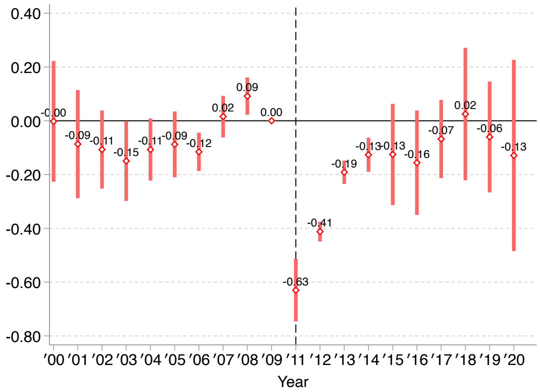
(a) Total landed amount (1000kg)



(b) Sales (1 million JPY)



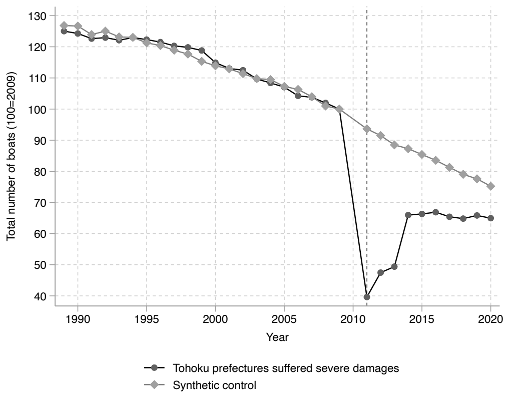
(c) Average price (1 JPY/kg)



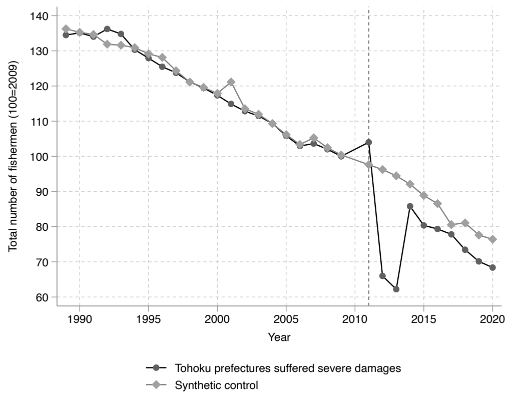
(d) Sales per fisher (1 million JPY)

Figure A4: Effects of the disaster on production inputs (excluding ports not participating in the survey (2011–2013))

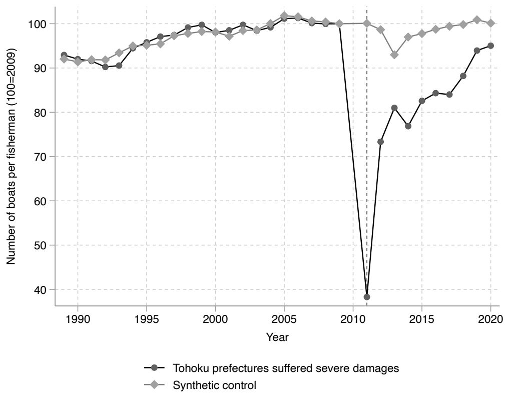
Note: We used all types of fish ports, except those located on remote islands, to create the figures. We also excluded ports that did not participate in the Topography of Fishery Ports survey at least once between 2011 and 2013. The dependent variables are log-translated. The markers indicate $\exp\left(\hat{\beta}_j\right) - 1$ for the year j, where $\hat{\beta}_j$ are the estimates of the cross term of the treatment dummy and the year dummy variables, and the bars are the 95 % confidence intervals for the estimates. The confidence intervals are calculated using standard errors robust against prefecture-level clustering (39 prefectures).



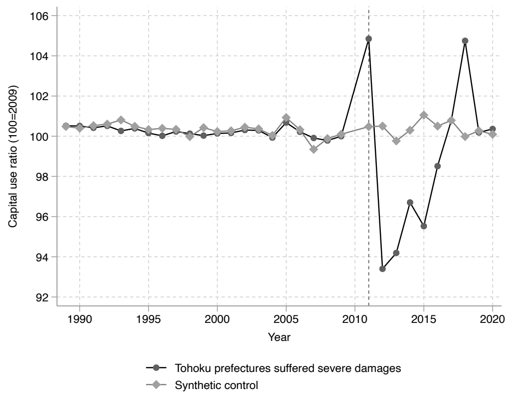
(a) Number of boats



(b) Number of fishers



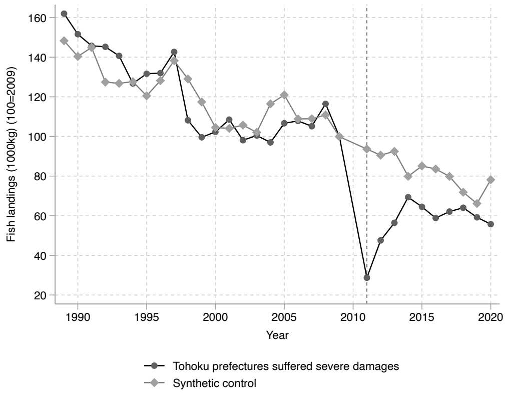
(c) Capital equipment rate (Boats per fisher)



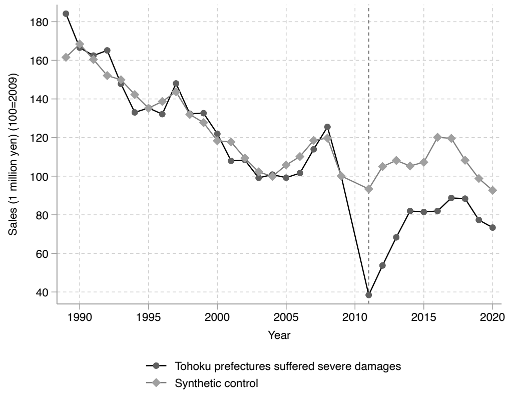
(d) Capital utilization ratio

Figure A5: Effects of the disaster on production inputs: Synthetic control method

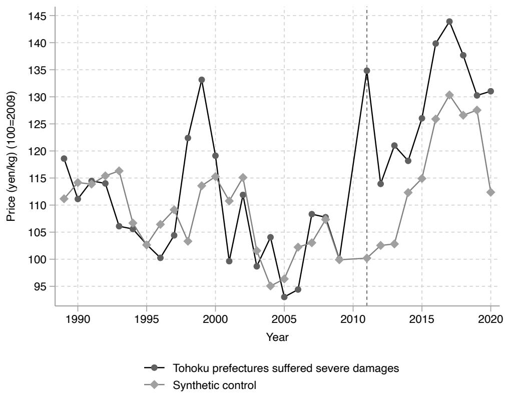
Note: We estimated the impact of the Tsunami attack due to the 2011 great earthquake using the synthetic control method. The donor pool consists of 32 prefectures with coastal lines except for Aomori, Ibaraki, Chiba, and Osaka prefectures. We used data in 1989 and 2009 to construct synthetic control. Table A1 summarizes the weights for synthetic control for each dependent variable.



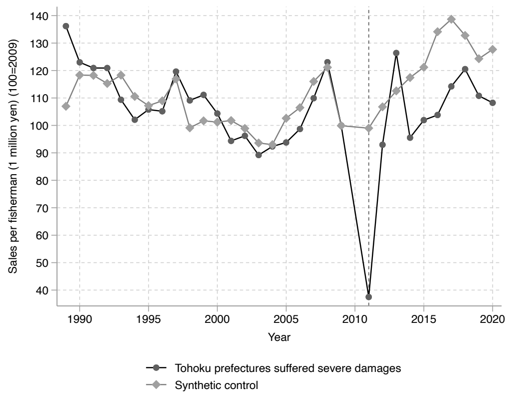
(a) Total landed amount (1000kg)



(b) Sales (1 million JPY)



(c) Average price (1 JPY/kg)



(d) Sales per fisher (1 million JPY/fisher)

Figure A6: Effects of the disaster on production outputs: Synthetic control method

Note: We estimated the impact of the Tsunami attack due to the 2011 great earthquake using the synthetic control method. The donor pool consists of 32 prefectures with coastal lines except for Aomori, Ibaraki, Chiba, and Osaka prefectures. We used data in 1989 and 2009 to construct synthetic control. Table A1 summarizes the weights for synthetic control for each dependent variable.

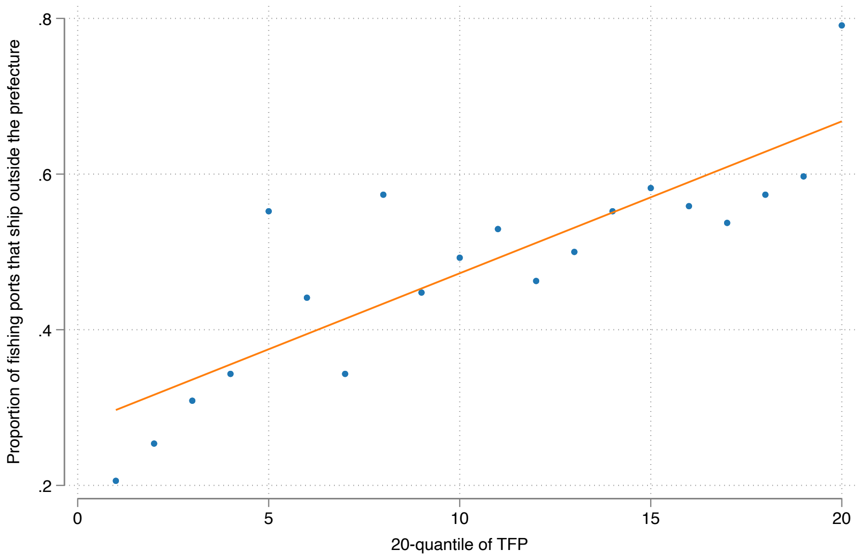
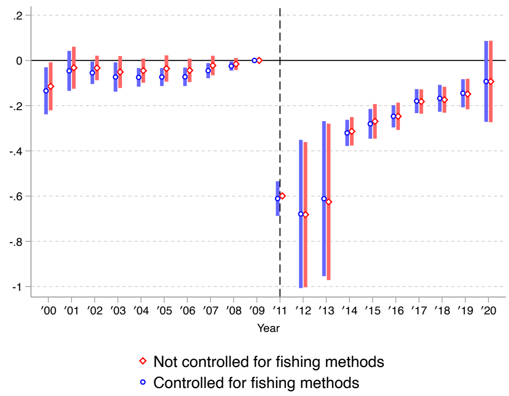
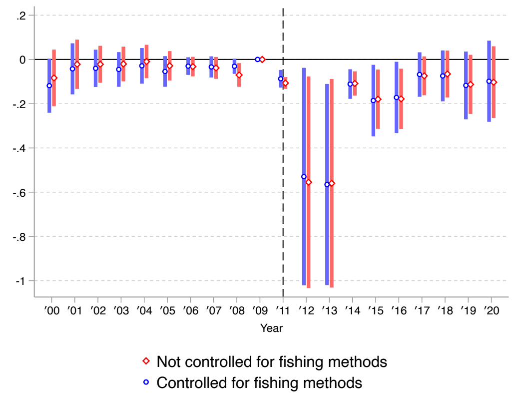


Figure A7: Proportion of fishing ports that ship outside the prefecture

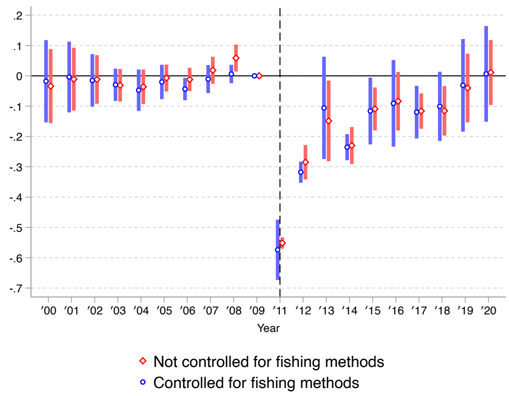
Note: The figure illustrates the relationship between port productivity and shipping destinations. The vertical and horizontal lines indicate the proportion of fishing ports that ship outside the prefecture and the productivity of ports, segmented by 20-quartiles.



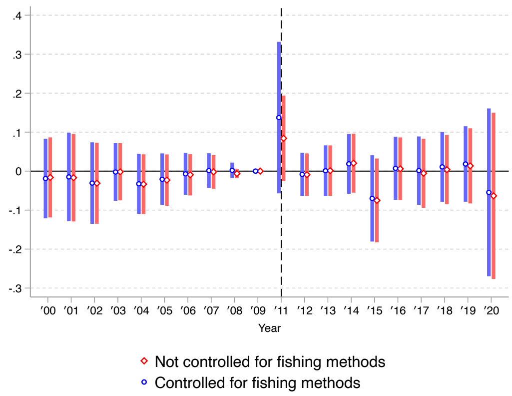
(a) Number of boats



(b) Number of fishers



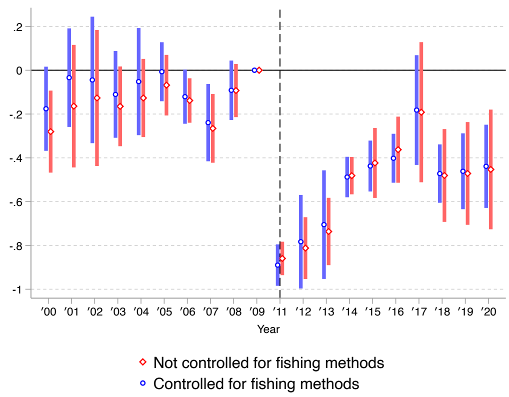
(c) Capital equipment rate (Boats per fisher)(T1)



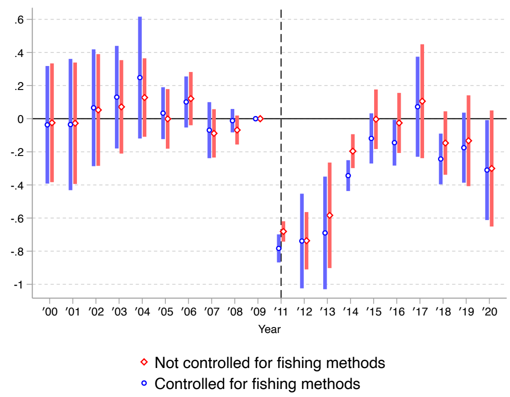
(d) Capital utilization ratio(T1)

Figure A8: Effects of the disaster by port-level TFP on inputs, controlling for composition of fishing methods (T1)

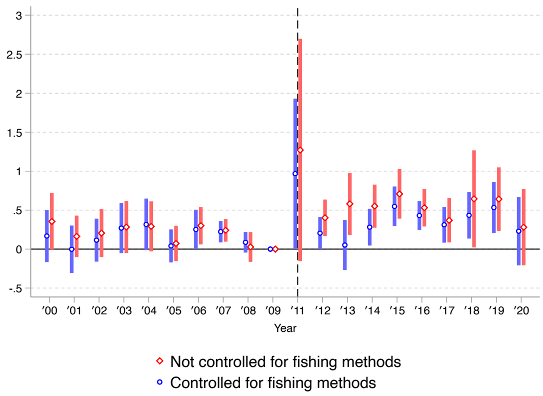
Note: We used all types of fish ports except those located on remote islands to draw the figures. The dependent variables are log-translated. The markers indicate $\exp\left(\hat{\beta}_j\right) - 1$ for the year j, where $\hat{\beta}_j$ are the estimates of the cross term of the treatment dummy and the year dummy variables, and the bars are the 95 % confidence intervals for the estimates. The confidence intervals are calculated using standard errors robust against prefecture-level clustering (39 prefectures).



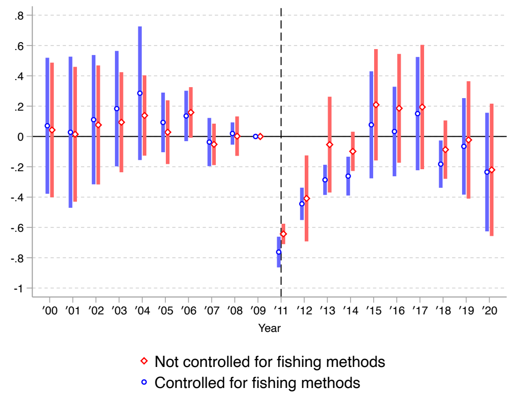
(a) Total landed amount (1000kg)



(b) Sales (1 million JPY)



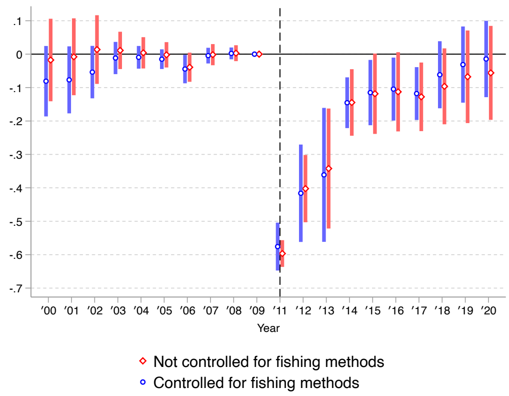
(c) Average price (1 JPY/kg)



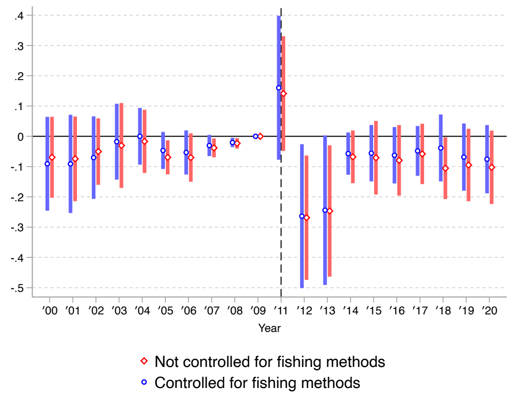
(d) Sales per fisher (1 million JPY)

Figure A9: Effects of the disaster by port-level TFP on outputs, controlling for composition of fishing methods (T1)

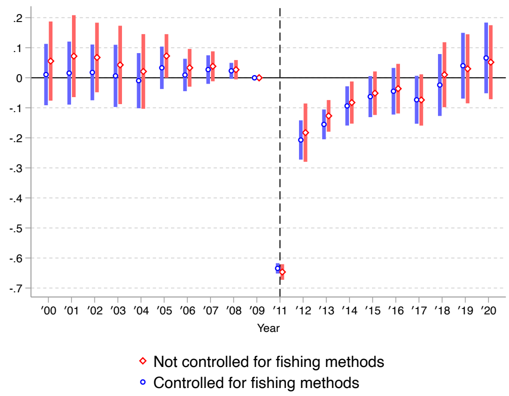
Note: We used all types of fish ports except those located on remote islands to draw the figures. The dependent variables are log-translated. The markers indicate $\exp\left(\hat{\beta}_j\right) - 1$ for the year j, where $\hat{\beta}_j$ are the estimates of the cross term of the treatment dummy and the year dummy variables, and the bars are the 95 % confidence intervals for the estimates. The confidence intervals are calculated using standard errors robust against prefecture-level clustering (39 prefectures).



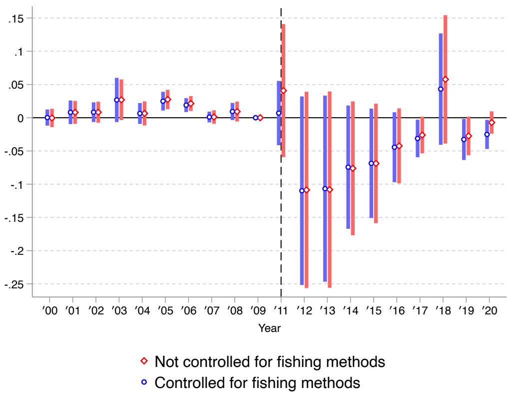
(a) Number of boats



(b) Number of fishers



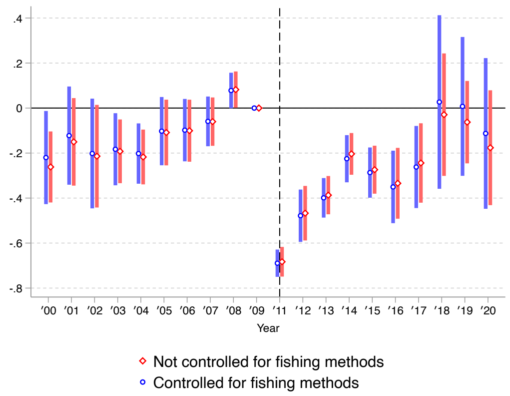
(c) Capital equipment rate (Boats per fisher)(T1)



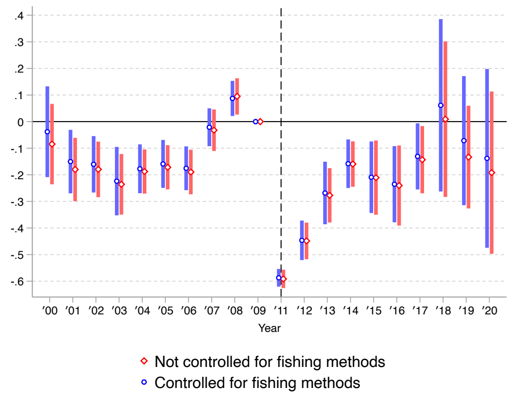
(d) Capital utilization ratio(T1)

Figure A10: Effects of the disaster by port-level TFP on inputs, controlling for composition of fishing methods (T3)

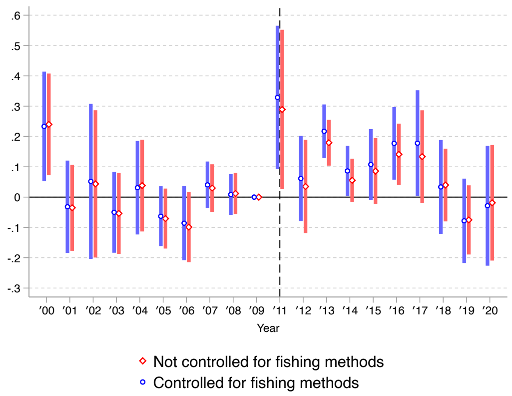
Note: We used all types of fish ports except those located on remote islands to draw the figures. The dependent variables are log-translated. The markers indicate $\exp\left(\hat{\beta}_j\right) - 1$ for the year j, where $\hat{\beta}_j$ are the estimates of the cross term of the treatment dummy and the year dummy variables, and the bars are the 95 % confidence intervals for the estimates. The confidence intervals are calculated using standard errors robust against prefecture-level clustering (39 prefectures).



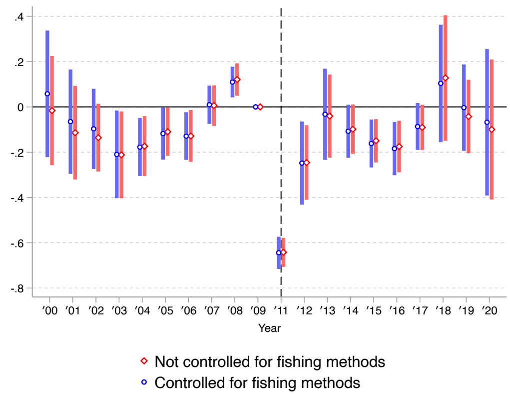
(a) Total landed amount (1000kg)



(b) Sales (1 million JPY)



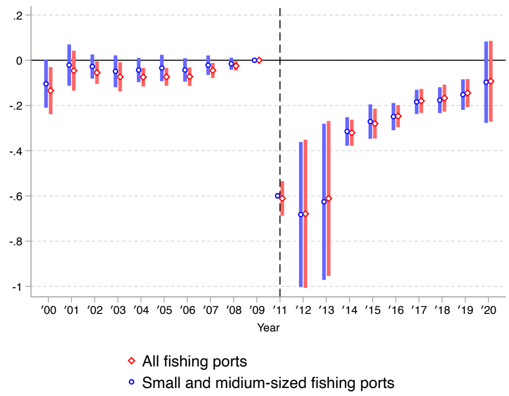
(c) Average price (1 JPY/kg)



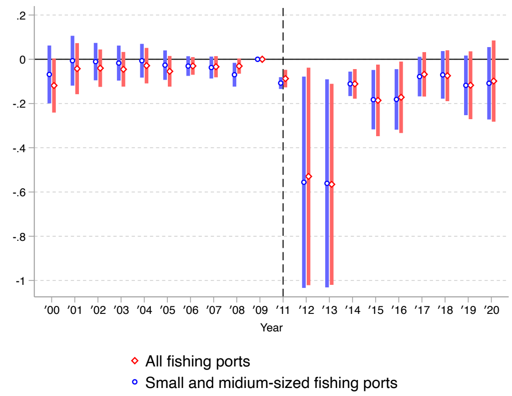
(d) Sales per fisher (1 million JPY)

Figure A11: Effects of the disaster by port-level TFP on outputs, controlling for composition of fishing methods (T3)

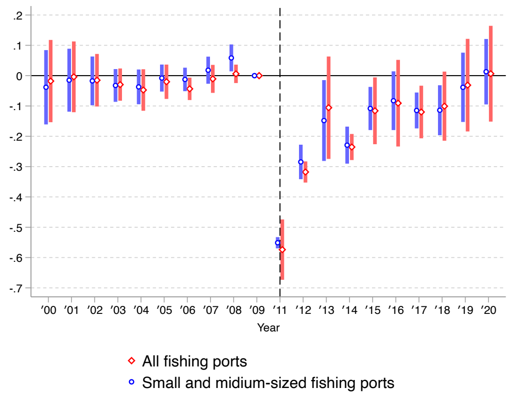
Note: We used all types of fish ports except those located on remote islands to draw the figures. The dependent variables are log-translated. The markers indicate $\exp\left(\hat{\beta}_j\right) - 1$ for the year j, where $\hat{\beta}_j$ are the estimates of the cross term of the treatment dummy and the year dummy variables, and the bars are the 95 % confidence intervals for the estimates. The confidence intervals are calculated using standard errors robust against prefecture-level clustering (39 prefectures).



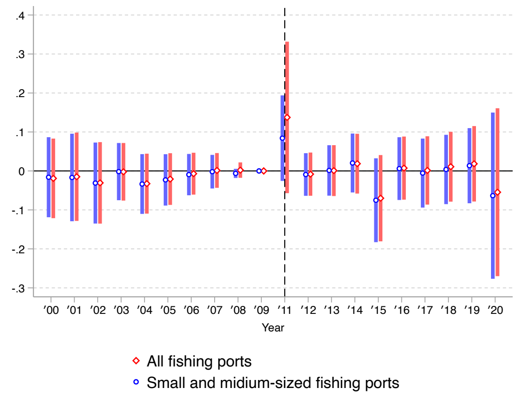
(a) Number of boats



(b) Number of fishers



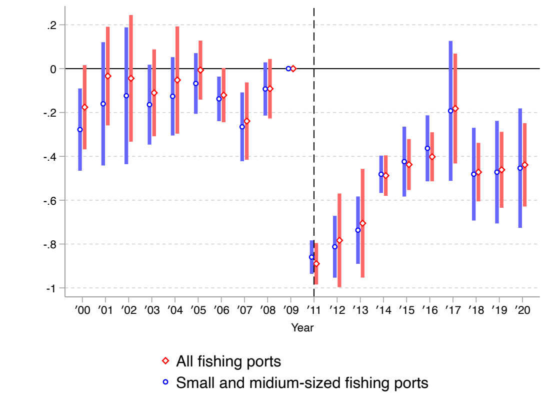
(c) Capital equipment rate (Boats per fisher)



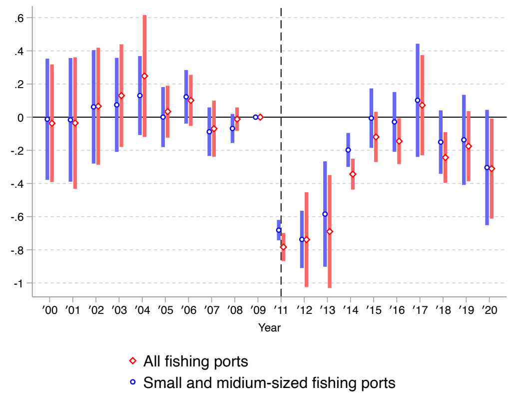
(d) Capital utilization ratio

Figure A12: Effects of the disaster by port-level TFP on inputs, excluding large ports (T1)

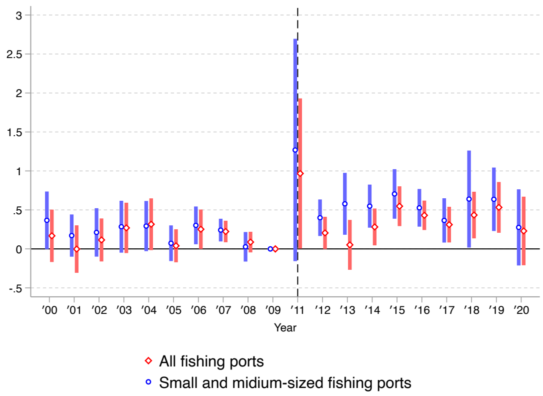
Note: We used all types of fish ports except those located on remote islands and those categorized as type-3 ports to draw the figures. The dependent variables are log-translated. The markers indicate $\exp\left(\hat{\beta}_j\right) - 1$ for the year j, where $\hat{\beta}_j$ are the estimates of the cross term of the treatment dummy and the year dummy variables, and the bars are the 95 % confidence intervals for the estimates. The confidence intervals are calculated using standard errors robust against prefecture-level clustering (39 prefectures).



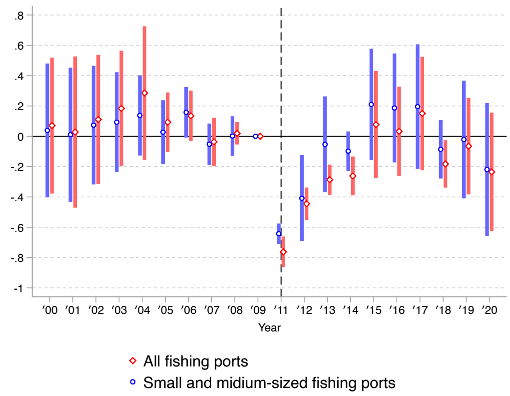
(a) Total landed amount (1000kg)



(b) Sales (1 million JPY)



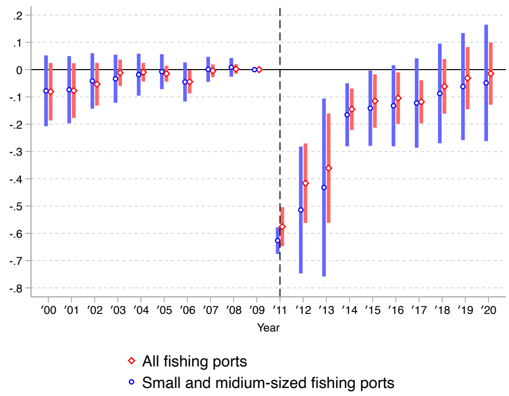
(c) Average price (1 JPY/kg)



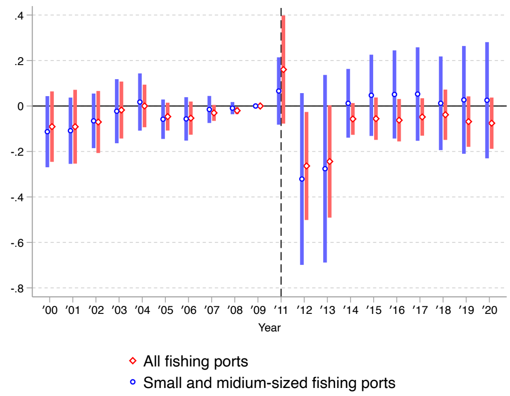
(d) Sales per fisher (1 million JPY)

Figure A13: Effects of the disaster by port-level TFP on outputs, excluding large ports (T1)

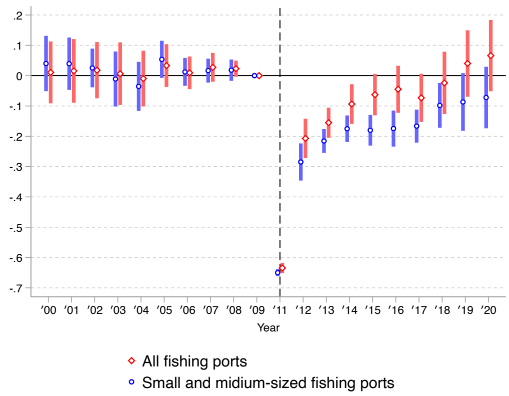
Note: We used all types of fish ports except those located on remote islands and those categorized as type-3 ports to draw the figures. The dependent variables are log-translated. The markers indicate $\exp\left(\hat{\beta}_j\right) - 1$ for the year j, where $\hat{\beta}_j$ are the estimates of the cross term of the treatment dummy and the year dummy variables, and the bars are the 95 % confidence intervals for the estimates. The confidence intervals are calculated using standard errors robust against prefecture-level clustering (39 prefectures).



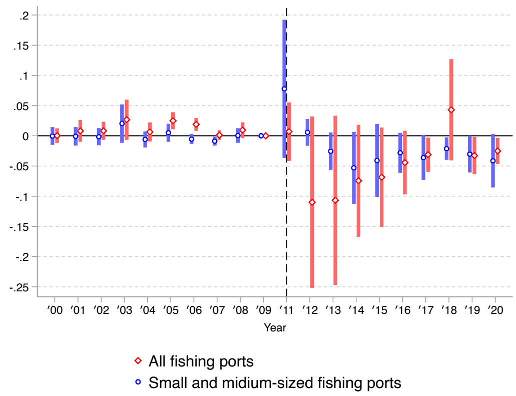
(a) Number of boats



(b) Number of fishers



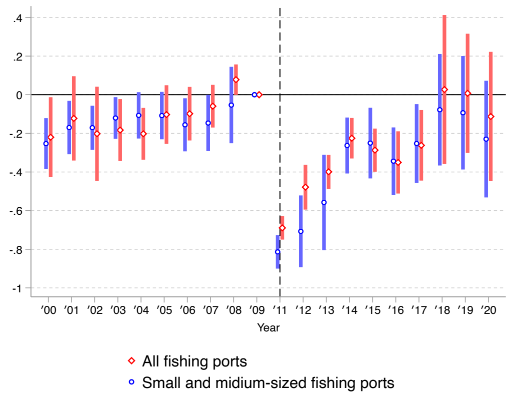
(c) Capital equipment rate (Boats per fisher)



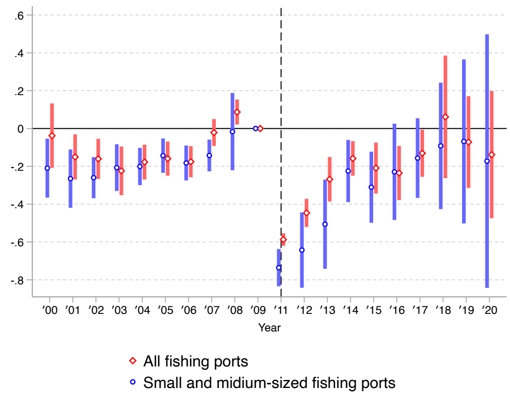
(d) Capital utilization ratio

Figure A14: Effects of the disaster by port-level TFP on inputs, excluding large ports (T3)

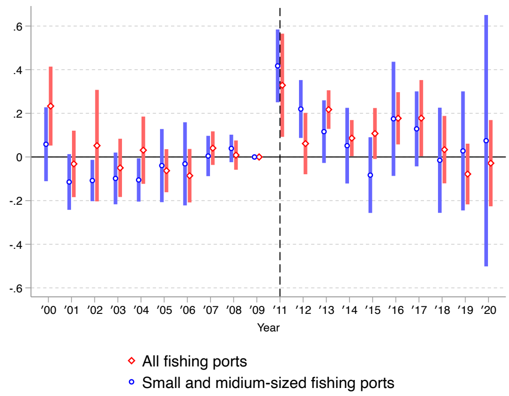
Note: We used all types of fish ports except those located on remote islands and those categorized as type-3 ports to draw the figures. The dependent variables are log-translated. The markers indicate $\exp\left(\hat{\beta}_j\right) - 1$ for the year j, where $\hat{\beta}_j$ are the estimates of the cross term of the treatment dummy and the year dummy variables, and the bars are the 95 % confidence intervals for the estimates. The confidence intervals are calculated using standard errors robust against prefecture-level clustering (39 prefectures).



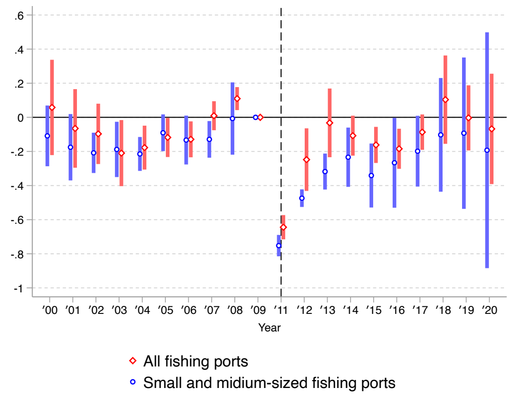
(a) Total landed amount (1000kg)



(b) Sales (1 million JPY)



(c) Average price (1 JPY/kg)



(d) Sales per fisher (1 million JPY)

Figure A15: Effects of the disaster by port-level TFP on outputs, excluding large ports (T3)

Note: We used all types of fish ports except those located on remote islands and those categorized as type-3 ports to draw the figures. The dependent variables are log-translated. The markers indicate $\exp\left(\hat{\beta}_j\right) - 1$ for the year j, where $\hat{\beta}_j$ are the estimates of the cross term of the treatment dummy and the year dummy variables, and the bars are the 95 % confidence intervals for the estimates. The confidence intervals are calculated using standard errors robust against prefecture-level clustering (39 prefectures).

Table A1: Weights for Synthetic Controls

	Boat	Fishermen	Boats per fishermen	capital use ratio	Fish landings (kg)	Fish landings (JPY)	Fish landings (JPY/kg)	Fish landings (JPY/fisherman)
Hokkaido	0	.037	.216	.002	0	0	0	.082
Akita	0	.001	0	.08	0	0	0	0
Yamagata	0	.13	0	.001	.227	0	.03	0
Tokyo	0	.01	0	.014	.151	.119	.129	.089
Kanagawa	.47	.017	.436	.077	.193	.294	.507	.383
Niigata	.138	.001	0	.001	0	0	0	0
Toyama	0	.005	.054	.002	0	0	0	0
Ishikawa	.123	.08	0	.001	0	0	0	0
Fukui	0	.151	.017	.09	0	0	0	0
Shizuoka	0	.007	0	.003	0	0	0	0
Aichi	0	.001	0	.005	0	0	0	0
Mie	0	.001	0	.003	0	0	0	0
Kyoto	0	.012	0	.072	0	0	0	0
Hyogo	0	.277	.189	.003	0	0	.006	0
Wakayama	0	.004	0	.006	0	0	0	.091
Tottori	0	.006	0	0	0	0	0	0
Shimane	0	.001	.008	0	0	0	0	0
Okayama	.056	.073	0	.08	.162	0	.019	0
Hiroshima	0	.003	0	.005	0	.007	0	0
Yamaguchi	0	.066	.08	.005	0	.138	0	0
Tokushima	.054	.008	0	.493	0	0	0	0
Kagawa	0	.001	0	.004	0	0	.053	0
Ehime	0	.004	0	.006	0	0	0	0
Kochi	0	.003	0	.004	0	0	0	0
Fukuoka	0	.001	0	.003	.222	0	0	0
Saga	0	.002	0	.006	.044	0	0	0
Nagasaki	0	.003	0	.004	0	0	0	0
Kumamoto	0	.082	0	.002	0	0	0	0
Oita	0	.007	0	.004	0	0	0	0
Miyazaki	0	.003	0	.019	0	0	0	0
Kagoshima	0	.004	0	.002	0	.443	.255	.354
Okinawa	.159	.003	0	.004	0	0	0	0

Table A2: Estimation result of Cobb-Douglas production function

	(1)	(2)	(3)
Log K	0.502***	0.482***	0.514***
	(0.051)	(0.048)	(0.053)
Log L	0.178***	0.180***	
	(0.036)	(0.036)	
Prop. Distant-water fishing		0.595**	
		(0.297)	
Prop. Offshore fishing		0.474***	
		(0.092)	
Prop. Aquaculture		0.793***	
		(0.117)	
Log L (15-34)			0.225***
			(0.039)
Log L (35-54)			-0.064
			(0.066)
Log L (55+)			0.026
			(0.061)
Observations	28587	28565	27306

We used the data from the pre-earthquake period (1989 to 2009). The unit of observation is the port. The dependent variable is logged value of the annual landing amount. The capital variable K is the sum of the registered boats with engines, and the labor variable L is the number of total fishers from the Topography of Fishery Ports. We multiplied the number of total fishers from the Topography of Fishery Ports by the ratio of fishers for each age category from the 2003 and 2008 Fishery Census. All models include the category variables of the fishery port's facilities (unloading place, ice making, frozen, refrigerated, ice storage, and oil supply). For each facility, we constructed the category variable with zero for missing and zero values, one for 0-25 %ile, two for 25-50 %ile, three for 50-75 %ile, and four for 75-100 %ile. We also used fishery port type-year fixed effects and prefecture-year fixed effects. Standard errors robust against port-level clustering are shown between parentheses. Inference: $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.