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Artificial creative destruction? The dynamic causal effect of the tsunami during the Great East Japan Earthquake

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Abstract

The 2011 Great East Japan Earthquake and tsunami is estimated as the costliest natural disaster to date, followed by Hurricane Katrina in the United States. By leveraging an instrumental variables approach using the historical tsunami monuments, this study estimates the short to long-run impacts of the tsunami on the subsequent economic activities proxied by nightlight intensity. The tsunami caused dynamic impacts in the affected areas: a significant fall in the first year, no robust effect in the second year, and positive impacts 7 years after that. Contrarily, the results also show a persistent negative on population size. Massive reconstruction funds on infrastructures are deemed to facilitate quick economic recovery in the affected areas, but they do not necessarily help people back to the affected areas.

Keywords: Tsunami damage, Creative destruction in the long run, The costliest natural disaster to date—the 2011 Great East Japan Earthquake, Japan, An instrumental variables approach
JEL Codes: O1-Economic Development, R11-Regional Economic Activity: Growth, Development, Environmental Issues, and Changes, Q54-Climate; Natural Disasters; Global Warming

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1. Introduction

The frequency and cost of natural disasters have increased in the world. During the 2010s alone, climate and weather-related natural disasters such as floods, storms, and heatwaves have impacted 1.7 billion people, and an additional 410,000 lives were lost (IFRC, 2020).

In addition to the significant number of casualties and the initial evacuees reaching about 0.47 million persons, among a number of natural disasters, the 2011 Great East Japan Earthquake and tsunami is the costliest natural disaster to date—the aggregated loss is estimated at $210-235 billion[2], followed by Hurricane Katrina in 2005, estimated at $161 billion[3]. Carvalho et al. (2020) discuss that the significant shock caused the decline of the real GDP of the four disaster-stricken prefectures in the 2011 fiscal year by 1.5 percentage point, and 0.47 percentage point for Japan's real GDP growth in the following year the disaster. The enacted government appropriation for the reconstruction has been more than twice the estimated damage by FY2020 for the Great East Japan Earthquake (roughly $472 billion, or JPY 38 trillion). The government appropriation for 2005's Hurricane Katrina reportedly exceeded $110.2 billion (U.S. Government Accountability Office, 2020). The injection of the funding for emergency relief and reconstruction efforts has been implemented quickly to save lives and recover from the disaster damages' direct and indirect economic losses. Meanwhile, the over-budget estimations for the relief and reconstruction have been pointed out as challenges—eroding public resources into unnecessary objects.

In academics, notably in growth literature, existing theories predict the subsequent economic trajectories after the external shocks, including natural disasters: (i) regional convergence hypothesis within a country based on neoclassical growth theory,

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[2] The estimated cost is based on the cabinet office of Japan and Ranghieri and Ishiwatari (2014). As of June 2011, the cabinet office estimated the direct cost at JPY 16.9 trillion (US$ 210 billion), of which JPY 10.4 trillion for buildings, JPY 1.3 trillion for lifeline utilities, JPY 2.2 trillion for social infrastructure, and JPY 3.0 trillion to others. Ranghieri and Ishiwatari's (2014) estimation indicated that the cost could reach up to US$ 235 billion.

[3] An estimate by National Oceanic and Atmospheric Administration (NOAA), retrieved on May 7, 2021 from the following URL: https://coast.noaa.gov/states/fast-facts/hurricane-costs.html

(ii) (Schumpeter's) creative destruction, and (iii) "Disaster trap" induced by poverty trap. First, the traditional neoclassical growth theory argues that the economic growth of the affected area converges to its steady state in the long run (Baumol, 1986; Barro and Sala-i-Martin, 1992a; Barro, 2015; Blattman and Miguel, 2010). In other words, the traditional neoclassical growth theory predicts that partial destruction by external shocks leads to the loss of both physical and human capital. Still, it does not affect the rate of technological progress. That is, the economy experiences the accumulation of capital in the affected areas (a short-term increase of investment resulted in a higher growth rate) and converges back to balanced growth steady states. Second, Schumpeter's creative destruction theory regards external shocks as an opportunity to grow more than the precondition (Aghion and Howitt, 1992).[4] This is because destruction may provide the opportunity for the affected area to introduce quality physical capital, leading to higher technological progress, which is supported by the empirical findings by Hornbeck and Keniston (2017), among others. Third, the disaster trap theory, induced by the concept of poverty trap developed by Azariadis and Drazen (1990), practically became widely used by the World Bank and Sachs (2005), which predicts the long-run negative effect of external shocks relative to the ex-ante condition. While there are some empirical supports for each theory, there is no unified answer. Thus, whether external shocks affect the long-run economic growth is ultimately empirical (Cavallo et al., 2013).

Despite the interests of policymakers and academics alike, empirical evidence on the impact of catastrophic natural disasters on the subsequent economic development in terms of economic growth and economic level is still limited mainly due to the lack of disaggregated statistics (i.e., growth indicators and disaster damage indices) as well as credible causal identification strategies.[5] In terms of statistics, first, subnational-level growth indicators are not readily available for many countries to capture detailed economic activities.[6] Natural disasters are typically localized issues, although being

[4] In the context of natural disasters, the "productivity effect," which is a similar idea to the creative destruction, has been mentioned, for instance, by Hallegatte and Dumas (2009), Benson and Clay (2004), Okuyama (2003), and Albala-Bertrand (1993).

[5] Aside from the effects on economic growth and economic level, there are a number of studies that link natural disasters and their effects, e.g., firm performance, employment, risk preferences of individuals, and sovereign debt. See the following literature on the effects on firm-level performance (Leiter et al., 2009; Basker and Miranda, 2018; Cole et al., 2019; Okazaki et al., 2019; Okubo and Strobl, 2020).

[6] Our understanding of the effects of natural disasters on economic development based on cross-country empirical evidence using aggregated data have been relatively matured (e.g., Cavallo et al., 2013; Loayza and Olaberria, 2012; Noy, 2009; Raddatz, 2007; Skidmore and Toya; 2002; Albala-Bertrand, 1993). Among those studies, Cavallo et al. (2013) used the synthetic control method and cross-country panel data

transmitted through supply chains. That is, coarse growth indicators such as a national GDP may hinder the rigor assessment of the spatially heterogeneous regional disaster impacts (see Strobl, 2011, 2012; Bertinelli and Strobl, 2013; Heger and Neumayer, 2019 that explicitly deal with the localized nature of natural disasters using sub-national growth indicators). Second, exogenous measurements of natural disaster impacts are challenging. Measures such as human causalities surveyed from survivors and the reported building losses are subjective indicators, and those indicators are likely to be susceptible to measurement errors. Although the number is still limited, some studies strived to find exogenous measures of disaster impacts on growth indicators (i.e., Hsiang and Jina, 2014; Strobl, 2011; Bertinelli and Strobl, 2013; and Heger and Neumayer, 2019). Lastly, on causal identification strategies, empirical investigations of the causal effects of natural disasters are hampered by the fact that more impoverished areas are likely to be hit harder. As Cavallo et al. (2013) discussed, estimating impact of natural disasters on economic development indicators in cross-sectional settings is likely to be biased upward in absolute value. Controlling for time-invariant unobservable variables using panel data partially alleviates the bias. However, it does not satisfy the assumption that disaster-struck areas equally grow, for example, at the pace of unaffected regions. Controlling for region-fixed effects would be helpful to control region-specific trends. However, it still does not fully control the region's more disaggregated socio-economic endowments. Cavallo et al. (2013) and Heger and Neumayer (2019) dealt with these issues of identification by employing a synthetic control method proposed by Abadie et al. (2010) to estimate the causal impact on growth indicators.

Our study overcomes these empirical challenges and contributes to the literature by adding new causal evidence of the short to long-term impacts of the tsunami during the 2011 Great East Japan Earthquake, which is the costliest natural disaster in world history. We do this by using the granular grid-level information comprising annual mean nighttime light intensity of about 1 km^2 from 2011 to 2018 and detailed tsunami inundation data extracted from aerial photos and satellite images. Using these, the analysis is performed at the most disaggregated level of administrative units, namely,

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covering 196 countries in the period 1970-2008, and find no significant impact on economic growth. Given the localized nature of natural disaster impacts, some studies shift their focus to a single-country or within country analysis. Strobl (2011) performs an econometric analysis using the exogenous measures of the hurricane destruction index in the US, and found no effect on the national economic growth rate. Also, although the analytical framework is short-run only, Carvalho et al. (2020) quantified using input-output linkages as a mechanism for the propagation and amplification of earthquake/tsunami shocks and found that the Great East Japan Earthquake in 2011 resulted in a 0.47 percentage point decline in Japan's real GDP growth in the following year, 2012.

municipal. In Japan's case, the municipal administrative unit comprises cities, towns, villages, wards, special words (special wards of Tokyo), *seireishiteitoshi*, *chukaku-shi*, and *tokurei-shi*.

The main empirical strategy relies on an instrumental variables approach—the intensity of the tsunami is instrumented by the number of historical tsunami-related monuments. Although we use the relatively precise tsunami inundation data derived from aerial photos and satellite images, the instrumental variable strategy would be necessary as the data could be still prone to measurement errors, e.g., technical issues such as the limited resolution of aerial photos/satellite images, and human errors during the data compilation. Further, the inundation areas themselves could be endogenous, meaning the inundated areas may tend to collect more significant amounts of reconstruction funding after the tsunami, leading to a higher growth rate.

In terms of the instrument's relevance, the number of municipal-level tsunami monuments is highly correlated to the tsunami inundation caused by the 2011 Great East Japan Earthquake (see also section 4.2.). However, concern remains on the violation of exclusion restriction—the location of tsunami monuments may represent areas with relatively more or less economic activities. To partially alleviate this concern, we controlled for the population density before the tsunami on top of the prefecture-level fixed effects. The decisions to construct tsunami monuments should be randomly determined, underpinned by the voluntary will of people, and often by donations. They should not systematically correlate to organized behaviors of local governments and private agents that affect the future economic trajectories through reconstruction investments in particular. However, ultimately, no established test definitively investigates instruments' validity in the context of exclusion restriction (Kiviet, 2020).

The remainder of this paper is organized as follows. Section 2 summarizes the background about the tsunami during the 2011 Great East Japan Earthquake and related literature. Section 3 describes the data and methodology. Section 4 presents the analytical results, their robustness and possible mechanisms. Section 5 concludes the paper.

2. Background: Tsunami at the 2011 Great East Japan Earthquake

The fourth largest earthquake in history with a magnitude of 9.0-9.1 hit the northeast coast of Japan at 2:46 PM JST (5:46 UTC) on March 11, 2011.[7] It triggered the destructive tsunami with a height reaching nearly 10 meters in the intensively struck locations in Miyagi, Iwate, and Fukushima. It has resulted in 561 km^2 of total inundation. More specifically, the maximum tsunami height was 14.8 meters at the Megawa Fishing Port in Miyagi, the tsunami run-up height was a record high at 40.5 meters, and the maximum distance from the coastal line was about 5 km in Sendai plain, according to the government of Japan. Further, although it is out of the purview of the main analysis of this paper, the tsunami caused another disaster, the leakage of nuclear radiation from the Fukushima Dai-ichi Nuclear Power Plant. We show that the location of the nuclear incident is a small fraction of tsunami inundation and does not statistically affect the tsunami-induced economic growth effects after that, as the spatial distribution differs.

Even ten years after the tragedy, the direct and indirect losses from the damages are still an ongoing issue. The confirmed numbers as of March 2021 are the following: 15,900 total deaths, of which more than 90% is derived from tsunami (9,544 for Miyagi, 4,675 for Iwate, and 1,614 for Fukushima), 2,525 (1,214 for Miyagi, 1,111 for Iwate and 196 for Fukushima) missing persons and 38,139 evacuees[8] according to the National Policy Agency as of February 2022. On the physical damages, the Reconstruction Agency reported that approximately 122,000 buildings were completely destroyed, about 283,000 suffered severe damage, and another roughly 748,000 were partially damaged. Extensive damages are observed on the transportation infrastructures, roads, railways, and airports.

[7] Based on the compilation by USGS (https://www.usgs.gov/programs/earthquake-hazards/science/20-largest-earthquakes-world). Retrieved on December 24, 2021.

[8] The catastrophic earthquake and tsunami

3. Data and methodology

3.1. Data

Municipal-level administrative boundary

The analysis performs at the most disaggregated level of administrative units, namely, municipal. Japan's bureaucratic administrative division is divided into the following layers: national, regional, prefectural and municipal. The municipal comprises cities, towns, villages, wards, special words (special wards of Tokyo), *seireishiteitoshi*, *chukaku-shi*, and *tokurei-shi*. There are 2,321 municipals in Japan as of 2020.

Tsunami inundation

This study uses the dummy variable of whether municipal administrative boundary got inundated or not during the 2011 Great East Japan tsunami as a damage proxy caused by the tsunami intensity. Sekimoto et al. (2012) and the Center for Spatial Information Science, University of Tokyo, compiled the tsunami inundation data based on aerial photos and satellite images made by the Geospatial Information Authority of Japan. Panel B in Figure 1 shows the tsunami inundation in black, ranging from Aomori to Chiba, spreading about 930 kilometers.

Although researchers often use tsunami inundation as an exogenous proxy of tsunami intensity, the inundation dummy may not necessarily capture the level of tsunami intensity perfectly, e.g., a shallow tsunami inundation may not necessarily lead to the catastrophic loss of human lives and physical damage of capital stocks as discussed above.[9] Further, the inundation data could be prone to measurement errors due to technical issues such as limited camera resolution and human errors in the compilation. We correct these measurement errors by employing an instrumental variable approach.

[9] On physical damage, early engineering literature on tsunami intensity and building damage show that wooden houses and reinforced concrete buildings may collapse if the tsunami heights (tsunami inundation depth) reach 2 and 8 m, respectively (Shuto, 1993), which is validated by subsequent studies and reached a rough consensus for the scientific community and in practice. See Suppasri et al. (2013), among others, to summarize the literature on the relationship between tsunami intensity and building damages. In practice, based on Shuto (1993), Japan Meteorological Agency sends an advisory message to the public for precautionary behaviors if more than 0.2 meters of tsunami is predicted to arrive as the 0.2 meters threshold is deemed to prevent the smooth evacuation of people. See the criteria proposed by Shuto (1993) in the webpage of Japan Meteorological Agency, retrieved on December 29, 2021. https://www.jma.go.jp/jma/kishou/know/faq/faq26.html

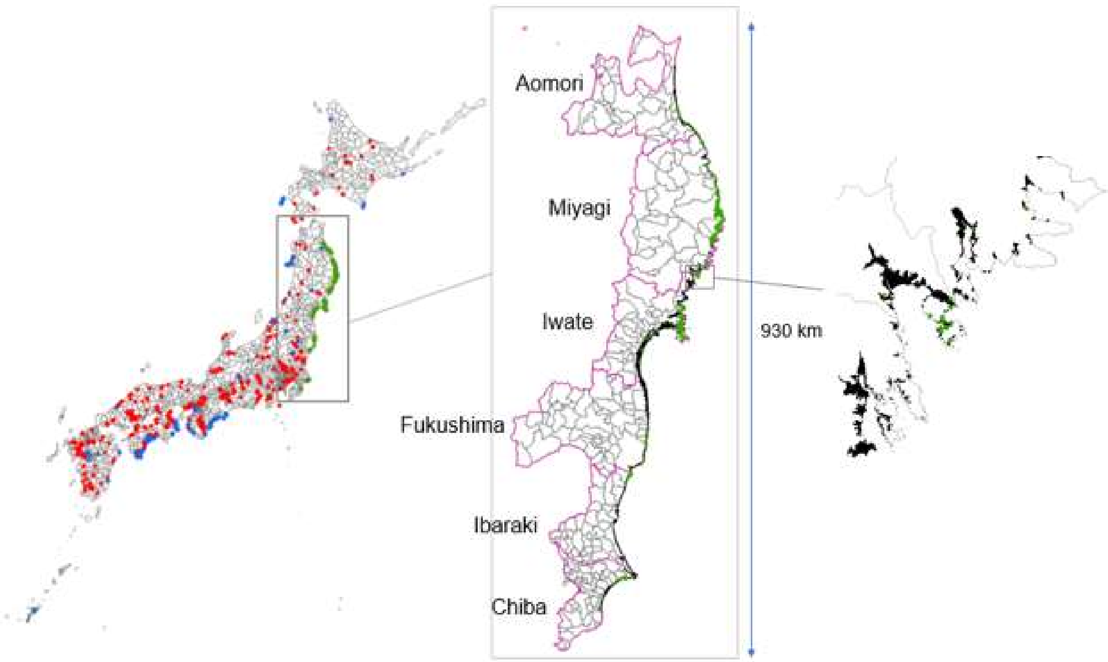
Historical tsunami monuments

The Geospatial Information Authority of Japan compiled the natural disaster monuments in Japan collected by local governments. The monuments depict the details of the tsunami disaster, such as name, the year the tsunami arrived, causalities and physical damages, and some lessons for future generations. Panel A in Figure 1 shows the spatial distributions of the tsunami monuments. The mark in green is the tsunami-related monument in the tsunami inundated prefectures during the 2011 Great East Japan Earthquake. The mark in blue is the tsunami-related monuments in the non-tsunami inundated prefectures. The mark in red is the monument of the other natural disasters.

Figure 1: The tsunami monuments and the tsunami-induced inundation by municipalities during the 2011 Great East Japan Earthquake

Panel A: The distribution of the tsunami-related monuments

Panel B: The tsunami-induced inundation and tsunami-related monuments in the tsunami-affected prefectures



Source: Geospatial Information Authority of Japan, Center for Spatial Information Science, University of Tokyo, and ESRI

Note: In Panel A, the mark in green is the tsunami-related monument in the tsunami-inundated prefectures during the 2011 Great East Japan Earthquake. The mark in blue is the tsunami-related monuments in the other prefectures. The mark in red is the monument of the other natural disasters. In Panel B, the area in black denotes the tsunami-induced inundation during the 2011 Great East Japan Earthquake.

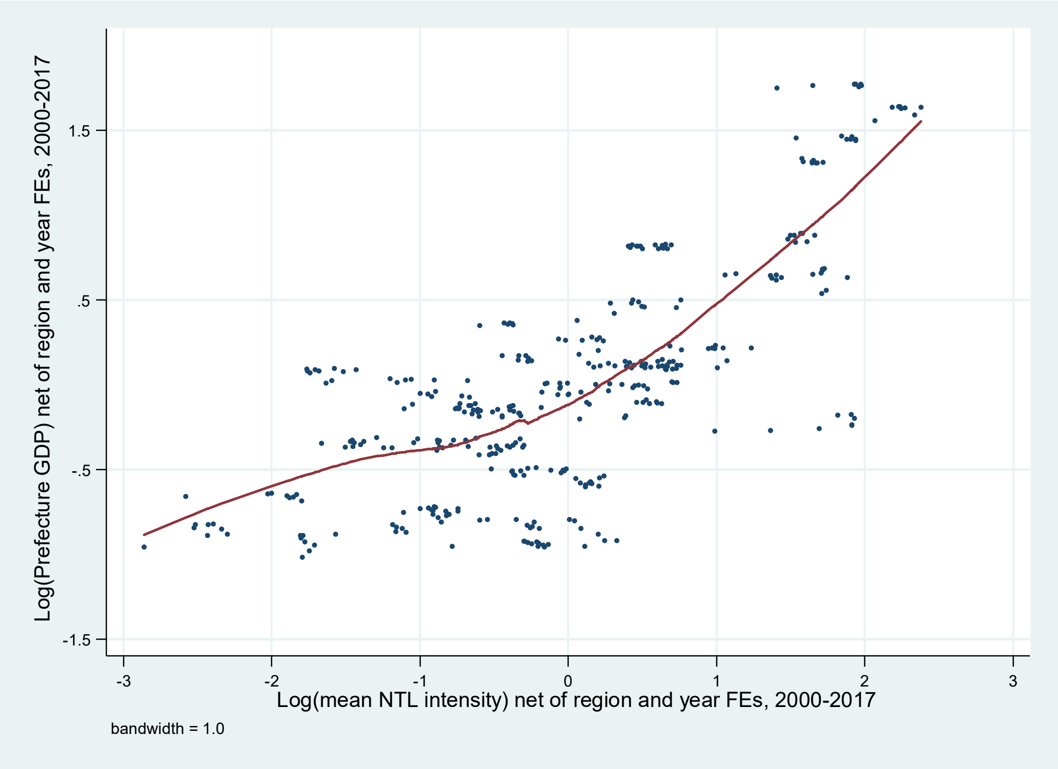
Nighttime lights

Leveraging the seminal finding by Henderson et al. (2012) that substantiates a strong correlation between variations in nighttime lights and economic growth rate by using panel data for around 190 countries from 1992–2008, this study uses nighttime lights data as a proxy of granular-level of economic activities. Specifically, we use a harmonized global nighttime light dataset 2000-2018 (Chen et al., 2021) compiled based on the Defense Meteorological Satellite Program (DMSP)/Operational Linescan System (OLS) and the Visible Infrared Imaging Radiometer Suite (VIIRS) on the Suomi National Polar-orbiting Partnership satellite. This harmonized dataset corrects the severe inconsistency between DMSP and VIIRS due mainly to the capacity difference of the monitoring sensors.

Satellite images are more accurate and objective than sectoral output data compiled by government authorities. Satellite images also enable us to capture smaller economic activities up to the grid level, allowing us to conduct municipal-level analyses. The DMSP products are available from 1992 to 2013 with 30 × 30 arc-second grids equivalent to approximately 0.86 km^2 at the equator, spanning −180° to 180° longitude and −65° to 75° latitude. Data values range from 0 to 63. VIIRS, available from 2012 to the present, further upgraded its resolution to 15 × 15 arc-second grids equivalent to around 0.5 m^2 at the equator with the same data coverage.

In the case of Japan, the prefecture-level GDP compiled based on the system of national account is highly correlated to the NTL intensity. The correlation after taking the logarithm is at 0.77 and the marginal effect in a linear OLS regression conditional on region and year fixed effects is 0.45 (95% CI: 0.30 – 0.60) at 1% statistical significance, meaning a 1% increase in the NTL intensity increases 0.45 percentage points of prefecture GDP. Without taking log transformations, the correlation is at 0.85, and the marginal effect in a linear OLS regression conditional on region and year fixed effects is JPY 2,182,405 (95% CI: JPY 710,224 – 3,654,586) at 1% statistical significance, indicating one increase in the NTL intensity digital number increases JPY 2,182,405 or roughly about US$ 20,000 of prefecture GDP.

Figure 2: The correlation between prefecture GDP and nightlights intensity conditional on region and year-fixed effects, 2000-2017



Source: Government of Japan, and the DMSP/VIIRS NTL data harmonized by Chen et al. (2021)
Note: The summary statistics of the DMSP/VIIRS NTL data harmonized by Chen et al. (2021) are the following: 5.9 (mean), 11.6 (standard deviation), 0 (minimum), and 112.7 (maximum). A caveat of this two-way scatter plot is that the prefecture GDP is only available in the fiscal year from April to March.

Population

This study uses the population census data for 2015 and 2020 from the Statistical Bureau of Japan. Although the population trend is declining, Japan had about 126.1 million of the population in 2020. Tokyo is the largest, with about 14 million population, followed by Kanagawa (9.2 million), Osaka (8.8 million), and Aichi (7.5 million). The prefectures heavily struck by the 2011 tsunami are much smaller in population, e.g., 2.3 million for Miyagi, 1.2 million for Iwate, and 1.8 million for Fukushima.

According to the National Police Agency, the 2011 Great East Japan Earthquake produced at least 15,900 deaths (9,543 for Miyagi, 4,675 for Iwate, and 1,614 for Fukushima) and 2,525 missing persons (1,214 for Miyagi, 1,111 for Iwate and 196 for Fukushima) as of March 2021. Among the deaths, 90.4% were due to drowning, likely to be induced by the tsunami.

3.2. Model specifications

To examine the year-by-year change of the average treatment effect of tsunami during the 2011 Great East Japan Earthquake on later short to long-term economic outcomes, an instrumental variable approach and a municipal-level cross-sectional dataset were employed to overcome the possibility of non-random spatial distributions of the tsunami as well as measurement errors in the tsunami inundation records assembled based on aerial photos and satellite images. We use OLS regression for reference to show the existence of estimation biases. As an instrument of the tsunami, we use the number of historical tsunami monuments.

In our empirical specification, as described in equation 1, we employ two types of data as outcome variables to investigate the dynamic chronological effects of the 2011 tsunami: mean nighttime light intensity from 2011 to 2018, and total population per km^2 in 2015 and 2020.

$$NTL\ or\ POP_{i,post-tsunami} = \alpha + \beta INUNDATION\_DUMMY_{i,2011} + \gamma CONTROLS + \delta_p + \varepsilon_i \quad (1)$$

Here the mean nighttime light intensity (NTL) for the years from 2011 to 2018 and the total population per km^2 (POP) in 2015 and 2020 of municipal i in prefecture p are the outcome variables; the inundation dummy caused by the 2011 tsunami for INUNDATION_DUMMY; the total population per km^2 in 2010 (before the 2011 tsunami) for CONTROLS; Prefecture fixed effects for δ; and the error term ε. The first stage estimation predicts the tsunami intensity by TSUNAMI_MONUMENTS as in equation 2.

$$\mathrm{I}NNUDATION\_DUMMY_{\mathrm{i},2011} = \mathrm{a} + \mathrm{b}TSUNAMI\_\mathrm{MONUMENTS} + \mathrm{c}CONTROLS + c_r + \mathrm{d}_i \quad (2)$$

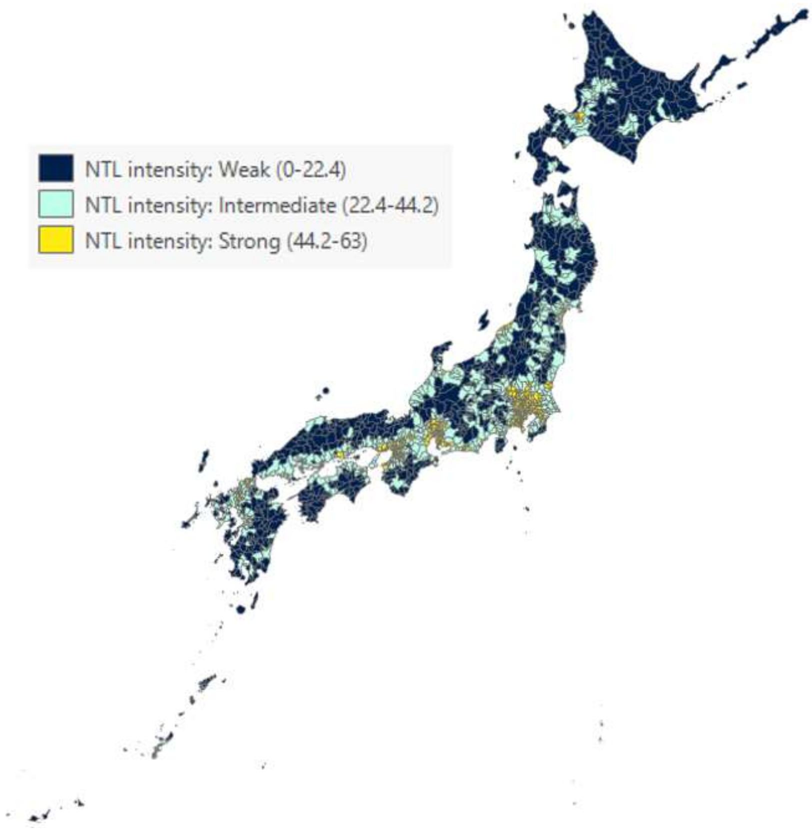
For the additional reference purpose, we use the difference in difference (DID) approach to capture the persistent effect of the tsunami using the municipal-level panel data. For more details, please see Appendix 2.

4. Analysis

4.1. The economic activities proxied by nighttime lights intensity: Before and after the 2011 Great East Japan Earthquake

Figure 1 shows the spatial distribution of the economic activities by municipal measured by nighttime light emissions in 2010 (before the 2011 Great East Japan Earthquake). There are three categories to distinguish the nightlight intensity: weak in dark blue (DN: 0-22.4), intermediate in light blue (DN: 22.4-44.2), and strong in yellow (DN: 44.2-63). Intense economic activities colored yellow concentrate on metropolitan areas like Tokyo, Aichi, and Osaka.

Figure 1: The magnitude of economic activities by municipalities in 2010, proxied by mean nighttime lights intensity

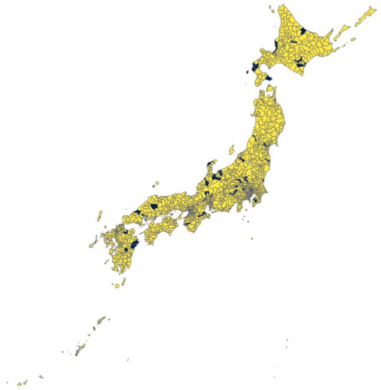


Source: DMSP and ESRI
Note: NTL intensity ranges from a minimum 0 to a maximum of 63.

In a country aggregation, the global financial crisis at the end of the 2000s triggered a strong economic downturn, with the growth rates at -1.2 and -5.7% in 2008 and 2009, respectively, according to the World Economic Outlook database April 2021. After that, the economy rebounded in 2010 with a growth rate of 4.1%, and the size of the economy measured by GDP in constant prices surpassed the pre-global financial crisis level in 2013, indicating that it took 4 years to bounce back to the pre-global financial crisis economic level.

Figure 2 similarly shows the nightlights growth rates from 2009 to 2010 and 2010 to 2011. After the global financial crisis, economic activities rebounded, reflected by the positive growth rate from 2009 to 2010 (Panel A). However, primarily due to the 2011 Great East Japan Earthquake, the growth rate became negative in the subsequent year (Panel B). Then, it bounced back with the mean growth rate of 0.04 from 2011 to 2012 (Panel C), but it declined slightly to 0.00 from 2012 to 2013 (Panel D).

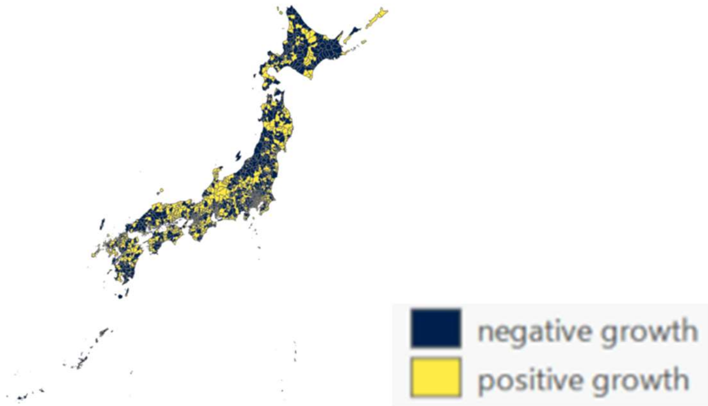
Figure 2: Average nighttime lights growth rate by municipal-level administrative boundary



Panel A: NTL growth rate between 2009-2010
(mean: 0.16, max: 0.83, min-0.34)

Panel B: NTL growth rate between 2010-2011
(mean: -0.12, max: 1.00, min: -1.10)

Panel C: NTL growth rate between 2011-2012
(mean: 0.04, max: 1.13, min-1.00)



Panel D: NTL growth rate between 2012-2013
(mean: 0.00, max: 0.60, min: -1.00)

Source: DMSP and ESRI
Note: NTL intensity ranges from a minimum 0 to a maximum of 63. The positive and negative growth is described in yellow and dark blue, respectively.

4.2. Predicting the tsunami intensity by the historical tsunami monuments

Table 1 shows the results of the first-stage estimation of the instrumental variables approach. The instrument, the number of historical tsunami monuments, shows a strong correlation to the tsunami inundation with a 1% level of statistical significance. Further, the instrument's relevance is confirmed by the Kleibergen-Paap rk Wald F statistic shown in the tables in the following subsections. As Staiger and Stock (1997) formalized, conventionally, 10 is a threshold for the weak instrumental variable test. In our case, most Kleibergen-Paap rk Wald F statistics exceed 80.

Table 1: Predicting the tsunami intensity by the historical tsunami monuments

	(1)	(2)	(3)
	Tsunami inundation		
IV: Tsunami monuments	0.975***	0.806***	0.806***
	(0.0150)	(0.0230)	(0.0892)
Control: Pre-tsunami total population per km^2			
in 2010		0.00408*	0.00408
		(0.00234)	(0.00499)
Prefecture fixed effects		✓	✓
S.E. clustered at the prefecture-level			✓
Observations	1,993	1,975	1,975
R-squared	0.678	0.748	0.748

Source: Geospatial Information Authority of Japan, Statistics Bureau of Japan, Center for Spatial Information Science, University of Tokyo, ESRI, DMSP/VIIRS NTL data harmonized by Chen et al. (2021).
Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the prefecture-level are in parentheses.

4.3. The economic impact of the tsunami during the Great East Japan Earthquake

Table 2 shows the year-by-year dynamic effect of the tsunami on nightlight intensity using OLS regression (Panel A) and the instrumental variables approach (Panel B).

In 2011 and 2012, in Panel A, the inundation dummy negatively affected the nightlight intensity at 10% statistical significance. However, the effects statistically disappeared after that. In 2018, the effect became positive with 5% statistical significance, implying that the tsunami-affected municipalities grew more than the unaffected ones.

In the two-stage estimations, the instrument's relevance holds for all the specifications according to Kleibergen-Paap rk Wald F statistics. The results show that the inundation dummy negatively affected the nighttime light intensity in 2011 at 5% significance. However, the effects statistically disappeared after that. In 2018, the effect became positive. These are consistent with the results using OLS regressions. To sum up, the two-stage estimation results show the dynamic change of the tsunami impacts: significant fall in the first year of the tsunami, no robust effect in the following years, and positive impacts 7 years after that, as graphically shown in Figure 3.

We run the same specifications depending on with and without Fukushima dummy on the impacts on population density in Table 3. In the case of Fukushima, in addition to the tsunami, the leakage of nuclear radiation caused a significant impact on the mass evacuation of people that affected the population size. Therefore, we controlled the Fukushima prefecture dummy in columns 1 and 2. The two-stage estimation results indicate the persistent negative impacts on the population density in 2015 and 2020, even after controlling for the Fukushima dummy. These results contrast against the nighttime light intensity in columns 3 and 4.

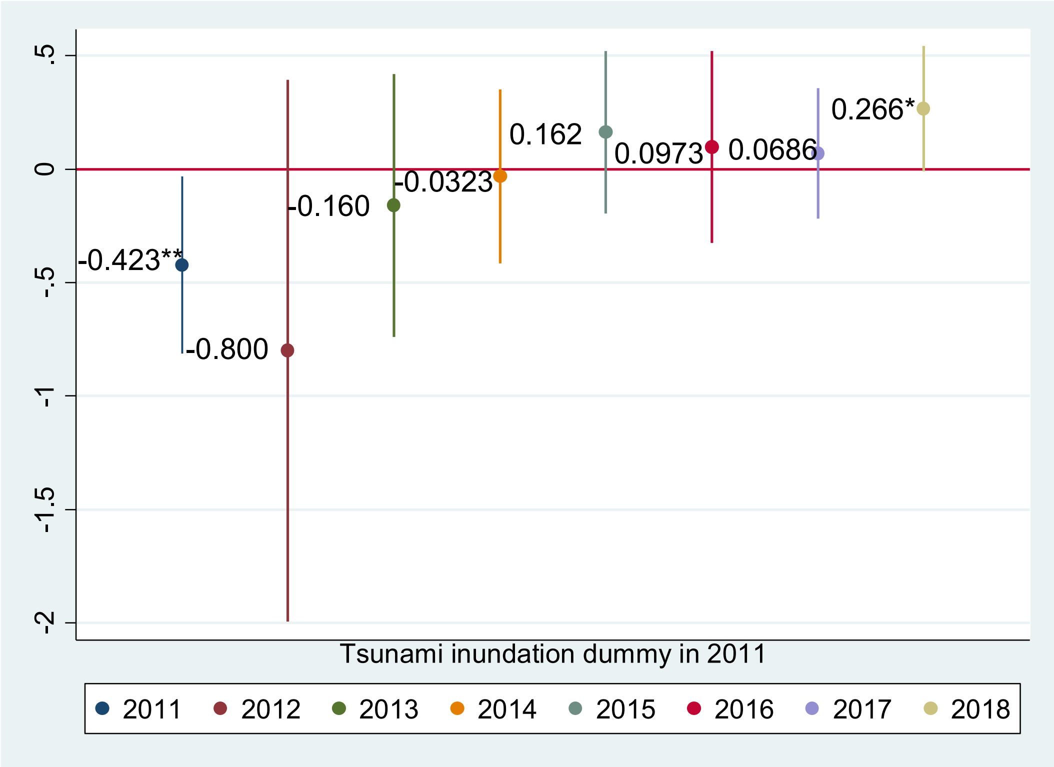
Table 2: The chronological change of the effects of the tsunami on nighttime lights intensity by municipalities from 2011 to 2018

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) OLS
	Dependent variable: Log nighttime light intensity							
	2011	2012	2013	2014	2015	2016	2017	2018
Panel A: The estimation results using OLS regression								
Tsunami inundation dummy in 2011	-0.301*	-0.587*	0.00347	0.0765	0.195	0.185	0.150	0.270**
	(0.179)	(0.328)	(0.186)	(0.147)	(0.139)	(0.165)	(0.131)	(0.123)
Pre-Tsunami population density in 2010	✓	✓	✓	✓	✓	✓	✓	✓
Prefecture fixed effect	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1,893	1,915	1,933	1,930	1,928	1,926	1,945	1,941
R-squared	0.901	0.905	0.926	0.927	0.929	0.925	0.932	0.935
Panel B: The estimation results using the IV/2SLS approach								
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	IV/2SLS	IV/2SLS	IV/2SLS	IV/2SLS	IV/2SLS	IV/2SLS	IV/2SLS	IV/2SLS
Tsunami inundation dummy in 2011	-0.423**	-0.800	-0.160	-0.0323	0.162	0.0973	0.0686	0.266*
	(0.199)	(0.610)	(0.295)	(0.196)	(0.182)	(0.216)	(0.147)	(0.141)
Pre-Tsunami population density in 2010	✓	✓	✓	✓	✓	✓	✓	✓
Prefecture fixed effect	✓	✓	✓	✓	✓	✓	✓	✓
Kleibergen-Paap rk Wald F statistic	81.6	80.9	81.0	81.6	81.6	76.1	81.6	81.6
Observations	1,893	1,915	1,933	1,930	1,928	1,926	1,945	1,941

Source: Geospatial Information Authority of Japan, Statistics Bureau of Japan, Center for Spatial Information Science, University of Tokyo, ESRI, DMSP/VIIRS NTL data harmonized by Chen et al. (2021)

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors, clustered at the prefecture-level, are in parentheses.

Figure 3: The chronological change of the effects of the tsunami on nighttime light intensity by municipalities from 2011 to 2018



Source: Geospatial Information Authority of Japan, Statistics Bureau of Japan, Center for Spatial Information Science, University of Tokyo, ESRI, DMSP/VIIRS NTL data harmonized by Chen et al. (2021)
Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors, clustered at the prefecture-level, are in parentheses. This figure shows the year-by-year change of the coefficient of tsunami inundation dummy instrumented by the number of tsunami monuments.

Table 3: Comparing the elasticity of the effect of the tsunami in 2011 on population density and nighttime light

	(1) IV/2SLS	(2) IV/2SLS	(3) IV/2SLS	(4) IV/2SLS
	Log population		Log nighttime light intensity	
	2015	2020	2015	2018
Tsunami inundation dummy in 2011	-0.0679**	-0.0787***	0.162	0.266*
	(0.0289)	(0.0272)	(0.182)	(0.141)
Pre-Tsunami population per squared km (log, 2010)	✓	✓	✓	✓
Prefecture fixed effect	✓	✓	✓	✓
Kleibergen-Paap rk Wald F statistic	81.6	81.6	81.6	81.6
Excluding Fukushima prefecture	✓	✓		
Observations	1,916	1,916	1,928	1,941

Source: Geospatial Information Authority of Japan, Statistics Bureau of Japan, Center for Spatial Information Science, University of Tokyo, ESRI, DMSP/VIIRS NTL data harmonized by Chen et al. (2021)
Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors, clustered at the prefecture-level, are in parentheses.

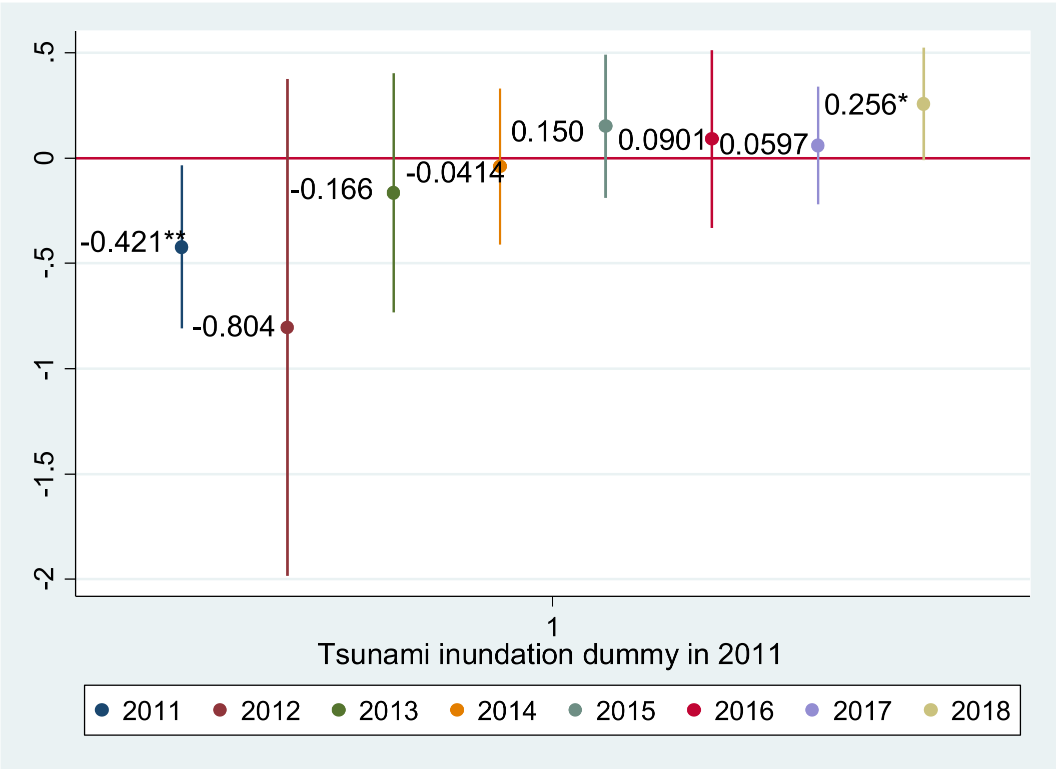
4.4. Robustness tests: Restricting the samples to only the prefectures that were affected by the tsunami in 2011

As a robustness test of the estimation results in Section 4.3, we run the same specifications using the limited samples by restricting to only the prefectures affected by the tsunami in 2011, namely Aomori, Miyagi, Iwate, Fukushima, Ibaraki, and Chiba.

Figure 4 shows the year-by-year change of the coefficient of tsunami inundation dummy instrumented by the number of tsunami monuments. Again, the instrument's relevance holds for all the specifications according to Kleibergen-Paap rk Wald F statistics that exceed 60. The results are qualitatively almost the same as the main estimation results, indicating that the tsunami negatively affected the economic activities proxied by the nighttime light intensity in the first year of the tsunami, with no robust effect in the following years, and turned out to be positive impacts 7 years after that.

We also confirmed the consistent estimation results to the main results by running the same specifications to see the tsunami impacts on population density using the subsamples.

Figure 4: The chronological change of the effects of tsunami on nighttime light intensity by municipalities from 2011 to 2018: Restricting the samples to only the prefectures that were affected by the tsunami in 2011



Source: Geospatial Information Authority of Japan, Statistics Bureau of Japan, Center for Spatial Information Science, University of Tokyo, ESRI, DMSP/VIIRS NTL data harmonized by Chen et al. (2021)

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors, clustered at the prefecture-level, are in parentheses. This figure shows the year-by-year change of the coefficient of tsunami inundation dummy instrumented by the number of tsunami monuments.

Table 4: Comparing the elasticity of the effect of the tsunami in 2011 on population density and nighttime light: Restricting the samples to only the prefectures that were affected by the tsunami in 2011

	(1) IV/2SLS	(2) IV/2SLS	(3) IV/2SLS	(4) IV/2SLS
	Log population		Log nighttime lights intensity	
	2015	2020	2015	2018
Tsunami inundation dummy in 2011	-0.0684**	-0.0799***	0.150	0.256*
	(0.0294)	(0.0265)	(0.173)	(0.136)
Pre-Tsunami population per squared km (log, 2010)	✓	✓	✓	✓
Prefecture fixed effect	✓	✓	✓	✓
Kleibergen-Paap rk Wald F statistic	60.8	60.8	65.2	65.1
Excluding Fukushima prefecture	✓	✓		
Observations	303	303	358	359

Source: Geospatial Information Authority of Japan, Statistics Bureau of Japan, Center for Spatial Information Science, University of Tokyo, ESRI, DMSP/VIIRS NTL data harmonized by Chen et al. (2021)

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors, clustered at the prefecture-level, are in parentheses.

5. Discussion on the mechanisms: Dynamic impacts of tsunami on later economic activities

The estimation results show that the tsunami triggered a significant economic fall in the first year, no robust effect since the second year, and positive impacts 7 years after that. This dynamic trajectory deems to reflect the progress of reconstruction activities through government public investments. Heavily struck prefectures, Miyagi, Iwate, and Fukushima, made a quick move and enacted the first line of the budget compilation for the reconstruction activities with the size of US$ 80.5 (JPY 1 trillion) for Miyagi, 40.3 billion (JPY 500 billion) for Iwate, and 56.4 (JPY 700 billion) for Fukushima within about 7 months after the March 2011 disaster destruction according to the Cabinet Office of Japan. The enacted government appropriation for the reconstruction has been more than twice the estimated damage by FY2020 (roughly US$ 472 billion, or JPY 38 trillion).

More specifically, the following primary lifelines and public services nearly recovered within about 3 months by June 2011, except specific areas such as the one within 20 kilometers of the Fukushima Daiichi Nuclear Power Plant, reported by the Reconstruction Agency: Electricity, gas, banking services, telecommunication, postal services, and gasoline stands. Although the reconstructions of the road network in Miyagi, Iwate, and Fukushima were mostly completed, and lifeline and public services were sound, as noted, the progress rate of the debris removal created by the catastrophic collapses of buildings and physical infrastructures was pretty limited at 6% in the first year (by the FY2011). This late progress of debris removal is deemed the bottleneck of economic recovery. That is, the first-year economic fallout from the tsunami, denoted in the previous analytical section, should reflect the tsunami's impact and the resulting slow pace of the reconstruction activities. Contrary, for the second year, the situation improved rapidly—the estimation results indicate no robust effects from the tsunami on economic activities. In reality, the debris removal progress rate reached 58% at the end of FY2012, along with the progress of (re)constructions of mega-road projects ranging to 570 km, coastal infrastructures, and public housing, among other things. Further, although it is not statistically significant, the estimation results turn positive in 2015 and onwards and finally become statistically significant in 2018. This implies tsunami-inundated areas show more robust economic activities on average compared to the non-tsunami-inundated areas, backed by the debris removal completion and varieties of capital investments stated above. The debris removal was completed at the end of FY2013 for Miyagi and Iwate, and at the end of FY2014 for Fukushima.

6. Conclusions

The fourth largest earthquake in history, with a magnitude of 9.0-9.1, hit the northeast coast of Japan on March 11, 2011. Even ten years after the tragedy, human losses and physical damages are still ongoing issues. Also, the 2011 Great East Japan Earthquake and tsunami is the costliest natural disaster to date, followed by Hurricane Katrina in 2005.

To our knowledge, Despite the interests of the policymakers and academics alike, empirical evidence on the localized impact of catastrophic natural disasters on the subsequent economic development in terms of economic growth and economic level is still limited mainly due to the lack of disaggregated statistics as well as credible causal identification strategies. Hence, this study asks whether the catastrophic tsunami affected later economic development in the case of Japan.

Our study leverages the granular grid-level information comprising annual mean nighttime light intensity of about 1 km^2 from 2011 to 2018 and detailed tsunami inundation data extracted from aerial photos and satellite images. By using these, the analysis is performed at the most disaggregated level of administrative units, namely, municipal, which capture the localized tsunami impacts. The primary empirical strategy relies on an instrumental variables approach—the intensity of the tsunami is instrumented by the number of historical tsunami-related monuments. Although we use the relatively precise tsunami inundation data derived from aerial photos and satellite images, the instrumental variable strategy would be necessary as the data could be prone to measurement errors. In addition, the inundation areas themselves could be endogenous, meaning the inundated areas may tend to collect more significant amounts of reconstruction funding after the tsunami, leading to a higher growth rate.

The estimation results show the dynamic change of the tsunami impacts: significant fall in the first year, no robust effect in the second year, and positive impacts 7 years after that. Contrarily, the results also show a persistent negative impact on the normalized population size. Massive reconstruction funds on public investments are deemed to facilitate the quick economic recovery in the affected areas. However, they still do not necessarily help people back to the affected areas even today. Economic recovery through massive (re)construction efforts worked in the case of Japan for economic recovery. Still, it remains the challenge: to recover the life of people who (had) lived in the affected areas.

Acknowledgements

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Appendix 1: Summary statistics of the inundation area in m^2

Appendix table 1: Summary statistics of the inundation area in m^2

Prefecture name	Municipal name	Obs.	Mean	SD	Max	Min
Miyagi	Sendai	5	9,439,638	15,300,000	36,000,000	12,847
Miyagi	Yamamoto	3	7,930,454	13,700,000	23,800,000	1,438
Miyagi	Watari	5	6,178,220	8,543,092	17,500,000	18,098
Miyagi	Iwanuma	8	3,187,169	4,537,279	12,900,000	740
Fukushima	Namie	3	1,803,338	1,544,515	3,184,812	135,782
Fukushima	Minamisoma	21	1,776,163	2,021,299	8,644,329	12,785
Ibaraki	Hokota	1	1,233,852	-	1,233,852	1,233,852
Fukushima	Soma	19	1,178,597	1,789,226	5,016,911	22,071
Miyagi	Natori	27	944,678	2,161,677	9,764,958	1,289
Ibaraki	Kashima	4	809,823	889,370	1,816,265	41,645
Ibaraki	Hitachinaka	2	806,773	288,359	1,010,674	602,873
Fukushima	Shinchi	11	801,784	801,634	2,299,649	1,256
Miyagi	Tagajyo	8	772,321	1,564,457	4,590,281	17,780
Miyagi	Shichigahama	9	535,547	956,543	2,956,629	5,090
Chiba	Sammu	20	478,390	1,294,626	5,312,962	2,203
Ibaraki	Kamisu	12	476,494	808,020	2,414,534	543
Fukushima	Iwaki	38	467,334	632,297	2,563,235	1,472
Fukushima	Naraha	6	433,102	513,708	1,398,922	44,166
Ibaraki	Oarai	4	409,173	802,419	1,612,698	148
Miyagi	Higashimatsushima	85	403,816	2,033,801	18,100,000	659
Miyagi	Ishinomaki	173	326,835	1,447,062	13,100,000	0
Ibaraki	Tokai	8	289,651	687,609	1,984,706	609
Iwate	Kamaishi	29	249,933	279,795	1,166,193	20
Fukushima	Tomioka	7	212,639	353,283	1,002,248	14,276
Miyagi	Kesennuma	86	201,446	605,205	3,855,502	0
Ibaraki	Kitaibaraki	10	200,893	277,289	870,439	1,291
Ibaraki	Hitachi	21	171,413	248,720	1,137,598	632
Ibaraki	Mito	4	122,161	239,847	481,921	121
Ibaraki	Takahagi	6	103,654	119,274	259,313	1,200
Miyagi	Megawa	42	78,235	249,031	1,601,564	2
Chiba	Ichinomiya	9	67,079	114,573	345,877	668
Miyagi	Shiogama	65	63,214	339,010	2,719,546	368
Miyagi	Matsushima	34	50,165	100,989	395,113	333
Miyagi	Rifu	5	37,907	34,934	91,204	5,785
Summary statistics		790	527,885	2,181,560	36,000,000	0.01

Source: Geospatial Information Authority of Japan and CSIS, University of Tokyo
Note: This table summarizes 790 available observations with detailed information on the inundation area in m^2 out of the 1,143 total observations.

Appendix 2: An alternative empirical strategy using DID

For reference purposes, we use a difference in difference estimation to capture the persistent effect of the tsunami using the municipal-level panel data. Dependent variables are log nightlight intensity or population density to reflect economic activities. The average treatment effect denotes the interaction term of the inundation dummy and a specific duration. We put three controls: prefecture-fixed effects, year-fixed effects, and prefecture-specific time trends. The prefecture and year interaction term denote the prefecture-specific linear time trend. The rationale for including the prefecture-specific linear time trend is to account for unobserved prefecture-specific features such as local-level business cycles or demographic trends.

$$
\begin{aligned}
&Log\ NTL\ or\ POP_{i,t} \\
&\qquad = \alpha + \sum_{k\geq 1} \beta_k \underset{k}{\ } Inundation\ has\ been\ in\ effect\ for\ k\ years_{i,t} \\
&\qquad + PREFECTURE\ FE_P \\
&\qquad + YEAR\ FE_t \left[+ \sum_{P} PREFECTURE_P * YEAR_t \right] + \varepsilon_i \quad \text{(A-1)}
\end{aligned}
$$

Appendix table 2: The average treatment effects of the tsunami using DID approach and all the samples

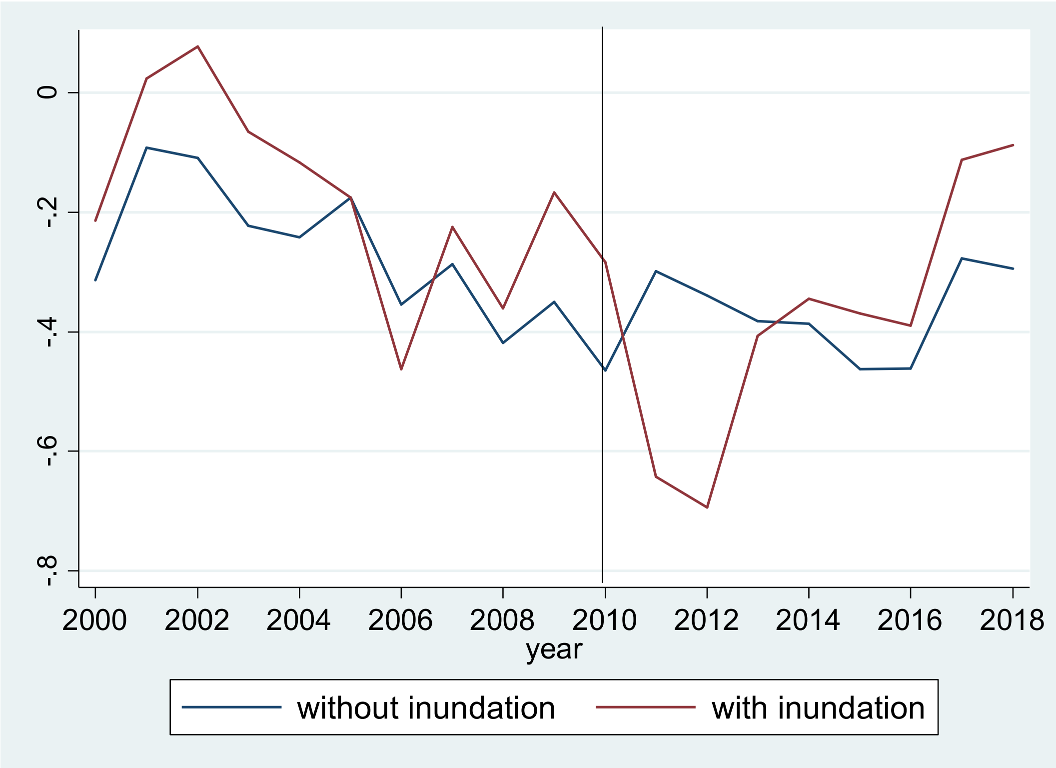
	Specifications	
	(i) Basic specification	(ii) Controlling prefecture-specific linear trend
First-year (2011)	-0.415***	-0.271**
	(0.111)	(0.125)
2011−2012	-0.444***	-0.379***
	(0.109)	(0.120)
2011−2013	-0.344***	-0.262**
	(0.0933)	(0.101)
2011−2014	-0.277***	-0.195**
	(0.0804)	(0.0909)

2011−2015	-0.225***	-0.135
	(0.0728)	(0.0865)
2011−2016	-0.196***	-0.0859
	(0.0667)	(0.0824)
2011−2017	-0.156**	-0.0552
	(0.0693)	(0.0894)
2011−2018	-0.115	-0.0120
	(0.0743)	(0.0992)
Year FE	✓	✓
Prefecture FE	✓	✓
Year×Prefecture		✓
Adjusted R-squared	0.439	0.445
Sample	2000-2018, n = 36,138 municipal-years	

Source: Geospatial Information Authority of Japan, Statistics Bureau of Japan, Center for Spatial Information Science, University of Tokyo, ESRI, DMSP/VIIRS NTL data harmonized by Chen et al. (2021)

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors, clustered at Prefecture-level, are in parentheses.

Appendix figure 1: The trend comparison of the log nighttime lights between the inundated municipalities and non-inundated municipalities using all the samples



Source: Geospatial Information Authority of Japan, Statistics Bureau of Japan, Center for Spatial Information Science, University of Tokyo, ESRI, DMSP/VIIRS NTL data harmonized by Chen et al. (2021)

Robustness tests: Restricting the samples to only the prefectures that were affected by the tsunami in 2011

To test the robustness of the estimation results using all the samples in equation A-1, we run the same specifications using only the samples of the tsunami-inundated prefectures, Aomori, Miyagi, Iwate, Fukushima, Ibaraki, and Chiba. The parallel trend is much better in this sub-sample. The estimation results are qualitatively the same using all the samples, meaning negative and statistically significant tsunami effects gradually vanish.

Appendix table 3: The average treatment effects of the tsunami using DID approach and the restricted samples within the inundated prefectures

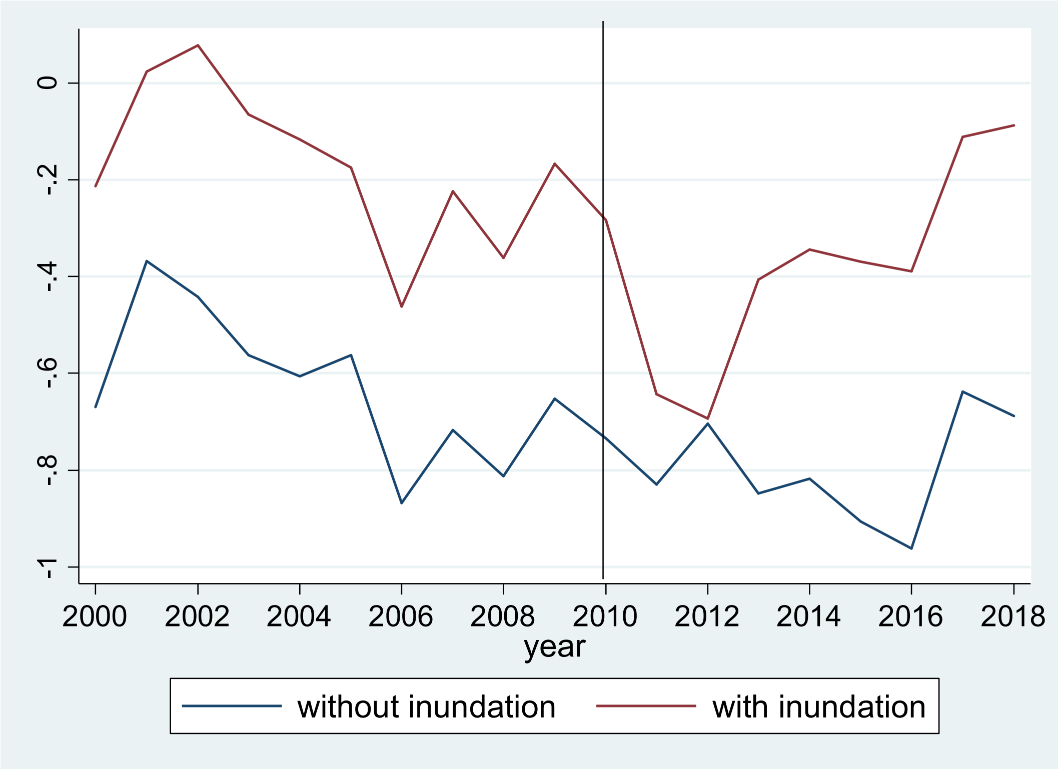
	Specifications	
	(i) Basic specification	(ii) Controlling prefecture-specific linear trend

First-year (2011)	-0.268*	-0.271
	(0.119)	(0.136)
2011−2012	-0.383**	-0.379**
	(0.117)	(0.130)
2011−2013	-0.271**	-0.262*
	(0.0939)	(0.109)
2011−2014	-0.207*	-0.195
	(0.0830)	(0.0984)
2011−2015	-0.151	-0.135
	(0.0769)	(0.0936)
2011−2016	-0.104	-0.0859
	(0.0719)	(0.0891)
2011−2017	-0.0768	-0.0552
	(0.0798)	(0.0967)
2011−2018	-0.0389	-0.0120
	(0.0907)	(0.107)
Year FE	✓	✓
Prefecture FE	✓	✓
Year×Prefecture		✓
Adjusted R-squared	0.429	0.432
Sample	2000-2018, n = 5,206 municipal-years	

Source: Geospatial Information Authority of Japan, Statistics Bureau of Japan, Center for Spatial Information Science, University of Tokyo, ESRI, DMSP/VIIRS NTL data harmonized by Chen et al. (2021)

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors, clustered at Prefecture-level, are in parentheses.

Appendix figure 2: The trend comparison of the log nighttime lights between the inundated municipalities and non-inundated municipalities by restricting the samples to only the prefectures that were affected by the tsunami in 2011



Source: Geospatial Information Authority of Japan, Statistics Bureau of Japan, Center for Spatial Information Science, University of Tokyo, ESRI, DMSP/VIIRS NTL data harmonized by Chen et al. (2021)