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The Fiscal Costs of Earthquakes in Japan

Abstract

We investigate the fiscal impacts of earthquakes in Japan. In contrast with earlier papers from elsewhere which examine national level aggregate spending, we are able to provide a detailed examination of separate budget categories within the local governments' fiscal accounts. We do this using detailed line-budget expenditure data, and by comparing regions and towns affected and unaffected by the damage from earthquakes. Besides the obvious - that government spending increases in the short-term (one year) after a disaster event - the results we present suggest that the share of public spending on disaster relief, at the prefecture level, increases significantly, but with no corresponding change in the other budget lines. In contrast, at the lower administrative units we observe a decrease in the share of spending going to finance other priorities. For the bigger cities, we observe a decrease in the share of spending targeting education, while for the smaller towns, we find that spending on construction and servicing public debt goes down. This evidence suggests that while at the prefecture level fiscal policy-making is robust enough to prevent presumably unwanted declines in public services, the same cannot be said for the city/town level.

JEL-Codes: H840, Q540.

Keywords: fiscal costs, earthquakes, Japan.

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1 Introduction

Disasters, i.e., catastrophic events that are triggered by natural hazards such as tropical cyclones or earthquakes, have myriad economic impacts. These impacts are identifiable in macroeconomic aggregates and in micro-economic data that follows individuals, households, and firms before and after the event. In the past decade, a large literature has attempted to quantify the macroeconomic impacts, emphasizing mostly the impact of disasters on GDP (as a general proxy for economic functioning). More recently, starting with Lis & Nickel (2010) and Noy & Nualsri (2011), several papers have attempted to quantify the fiscal impacts of disasters in cross-country comparisons and with various empirical approaches (VARs and panel VARs, diff-and-diff, etc.). These papers have typically emphasized the aggregate amount of fiscal spending after a disaster event, net expenditure (i.e., the deficit), tax and tariff revenue, or government borrowing and the evolution of the stock of debt in the disaster's aftermath (e.g., Melecky & Raddatz (2014), Mohan *et al.* (2018), and Klomp (2019)). They generally conclude, maybe not surprisingly, that government accounts deteriorate in a disaster's aftermath, while spending increases, tax revenue declines, debt increases, and the likelihood of a sovereign rating downgrade or even default rises.

Instead of using cross-country comparisons, a spate of recent studies have looked at sub-national fiscal aggregate spending, e.g., Miao *et al.* (2020) for China's provinces, Panwar & Sen (2020) for India's states, Karim & Noy (2020) for Bangladesh's sub-districts, Jerch *et al.* (2020) for US counties, and Unterberger (2018) for municipalities in Austria. We do the same for Japan, but, in contrast with these earlier papers, emphasize a detailed examination of the separate budget categories within the local fiscal accounts. Our contribution is therefore twofold: We analyse detailed data on different budgetary categories, and we trace the fiscal dynamics at a very detailed spatial scale (i.e., more than 1700 municipalities). We do this research by comparing prefectures and towns affected and unaffected by the damage from earthquakes.

The added value of our sub-national intra-country examination lies in our ability to delve deeper into the drivers of these aggregate changes in the fiscal accounts that result from the occurrence of disasters, rather than exclusively focus on quantifying the magnitude of the change. In one related precursor to our work, Deryugina (2017) examined the impact of hurricanes in the South Eastern US on the evolution of social spending in the affected regions. She finds that the increased spending on unemployment benefits and other social programs outweighed the direct spending on post disaster relief that followed these hurricanes. In addition, the social spending increases she documented persisted for a longer period than the direct disaster relief. As Deryugina (2017) observed, when examining the fiscal accounts of local authorities, one needs to account for transfers from central government, especially in countries where the center dominates fiscally through its ability to set and collect taxes. In this regard, del Valle *et al.* (2020) investigated the fiscal impact of central government transfers to local authorities in the aftermath of disaster events in Mexico. In the Mexican case such transfers are guided by predetermined rules in a program called FONDEN. In most cases, however, these transfers are ad hoc, and often dictated by political considerations, where congruent patterns were found in India by Cole *et al.* (2012), in China by Miao *et al.* (2020), and in the US by Healy & Malhotra (2009).

We focus on Japan, and ask what happens to local public spending by budget lines after a disaster. Japan is arguably an interesting case for several reasons. First, the most prevalent disaster type in Japan, the one we study here, is earthquakes. Unlike storms or floods - the hazard of note in almost all the papers cited earlier, earthquakes are not seasonal, their onset is random, and in Japan they can occur just about everywhere (though with differing and imprecisely assessed probabilities). Japan is the country most exposed to earthquake risk globally, and the one with the most earthquake disasters, so even with fiscal data for just a decade we can estimate their impacts. Second, Japan has uniformly collected and publicly available data on local spending by budget line, where similar data only exist for very few other countries. Rather, unlike Japan, most bigger countries have a federal structure, which typically precludes a uniform budgetary system. Third, Japan is highly centralized and has a hierarchical system of central government, prefectures and municipalities ("Shi-cho-shon" in Japanese, i.e. cities, towns and villages). Each body is responsible for different public services, and with some authority to collect taxes. Nevertheless, the central government is the most consequential level of governance, permitting only a small portion of autonomy for local governments by imposing regulations and top-down decision-makings (the so-called "30 percent local autonomy"). More precisely, instead of granting more power to the local authorities, the central government deploys various financial schemes, subsidies, and tax transfers to local governments, to ensure a uniform quality of public services across Japan. Fiscal spending after a disaster is not an exception to this in that the local governments are in charge of recovery and aid directly, but the central government provides several funding streams to aid them. In particular for large-scale disasters a special law dictates that the central government is required to provide special subsidies and provisions to local governments.

Our analysis relies on the official expenditure data available, combined with measured earthquake intensity, and modelled damages weighted by asset exposure. We use these panel data to estimate the impact of damages on fiscal expenditure using various levels of spatial dis-aggregation. Our results reveal a number of important differences across expenditure types and regional levels.

The next section provides information about the Japanese fiscal structure and practices related to spending, especially in the disaster recovery context. More explanations about the data and the methodology are available in the next two sections (sections 3 and 4, respectively). Section five describes our results, while section six discusses the implications of our findings, some caveats, and our direction for future research .

2 Background

2.1 Regional Units

Japan is very centralized, with a hierarchical system from central government, to prefectures, and then municipalities. We analyse the two regional classifications, prefectures and municipalities. There are 47 prefectures and 1,718 municipalities as of 2020. Of the 1,718 municipalities, Metropolitan Tokyo (the national capital) is the largest and has different spending powers. There were 15 'Designated' cities as of 2007 ("Seireishitei-toshi"); these are major cities with more than 500 thousands people. They include Sapporo, Sendai, Chiba, Saitama, Kawasaki, Yokohama, Sagamihara, Niigata, Shizuoka, Hamamatsu, Nagoya, Kyoto, Osaka, Sakai, Kobe, Okayama, Hiroshima, Fukuoka, Kitakyushu, and Kumamoto. There were 44 'Core' cities as of 2007 ("Chukaku-shi"), which are smaller than the designated cities and defined as cities with a population of more than 300 thousands.[1]

2.2 The Local Fiscal System

In Japan local government is responsible for the social and administrative infrastructure that determines much of daily life. Central and local government are thought of as the twin pillars of government spending (Ministry of Internal Affairs and Communication, 2020). In the 2018 fiscal year, 43 percent of total government spending (71.9 out of 169.2 trillion yen) was by central government while the rest was spent by the local authorities. The central government is responsible for spending on the military, foreign affairs, social insurance, universities, highways, major river-ways, and national roads, while the local government spends on local and regional roads, ports, public housing, urban planning, education, hygiene, health, water, local security and residential administration.

The two layers of the local government, prefectures and municipalities, are in charge of different administrative tasks. Prefectures spend on the management of public high schools, police, industrial waste, health care centers, pollution control, and urban planning. Municipalities finance the management of elementary and junior high schools, fire service, residential registration, sewage, water supply, and garbage disposal.

The Designated and Core cities have additional administrative responsibilities that are transferred to them from their prefecture. These include welfare programs (e.g. supervision of social welfare facilities), establishment of health care centers, urban planning, and environmental administration (e.g. industrial waste control, pollution control and water quality control).

[1] By 2020, there were 20 Designated cities and 62 Core cities. In 2014 the definition for Core cities was revised to be more than 200 thousands.

2.3 Disaster Spending by Local Government

In recent years, local government have had to increase their spending on post-disaster recovery costs. In particular, during the last decade Japan has experienced a large number of damaging disasters, starting with the catastrophically costly earthquake and tsunami (the Great East Japan Earthquake) of March 11, 2011 ,and continuing with typhoons, heavy rains, and several other earthquakes.

Japan has a long history of legislated post-disaster management, in particular with respect to fiscal spending allocations.[2] Some laws on the rescue of victims from disasters even date back to the 1870s. In 1899 the Law for Relief Funds was enacted, which specified the funding system for the local government, and the coverage of spending for rescue and recovery. After WWII, the Disaster Relief Act was enacted in 1947, where the local government was placed in charge of spending on recovery from disasters, with some support provided by the central government.[3] Later, the management by the central government was clearly specified in the Disaster Countermeasures Basic Act of 1961, which was enacted after a super-typhoon, namely the Ise Bay typhoon that hit Nagoya City in 1959 (Okubo & Strobl, 2020). The law outlined co-ordination for disaster prevention and post-disaster management by the central government. Subsequently, the Act concerning Special Financial Support to Deal with Designated Disasters of Extreme Severity was established in 1962, which specified the financial support that will be provided by the central government to municipalities when they experience a catastrophe.

More recently, several reforms of the fiscal allocation system have been completed since the Kobe earthquake of 1995. The fiscal aid and compensation responsibilities of the

[2]See also Cabinet Office (2002) for the history of disaster management policies in post-war Japan.

[3]According to the Act, municipalities spend the cost for recovery in the case of small disasters, but prefectures mainly pay for the cost of large disasters.

central government were clarified and strengthened. The central government now compensates disaster victims more. The central government also provides more financial support for recovery plans made by municipalities. In addition, by strategically using contingency funds in the national budget, the central government can immediately supply emergency financial aid to local governments within 3 days after a disaster.[4] These large scale financial aid policies are financed by issuing bonds and/or by increasing taxation.

3 Methodology

3.1 Damage Modeling

To model earthquake damage we utilize the same model used in Skoufias *et al.* (2021)[5] where earthquake maps of peak ground acceleration are combined with vulnerability curves, localized exposure, and building data to model annual damages. More precisely, regional level earthquake damages ED in year t are constructed from local damage curves and exposure:

$$ED_{r,t} \equiv \sum_{e \in E} \sum_{i \in r} W_{i,r,t-1} ED_{e,i,r,t} \tag{1}$$

where $e \in E$ are a set of earthquakes that take place in year t, $i \in r$ are a set of locations in region p, and W is an asset exposure weight. To construct local measures of earthquake damage we use damage ratios DR that are building type b specific and depend on peak

[4]On the revenue side, the central government allows firms to reduce tax payments on pre-disaster investments. Once a disaster happened, damaged firms and households are allowed to reduce and/or waive some tax payments.

[5]We note that Skoufias *et al.* (2021) used this damage algorithm to examine whether nighttime lights can by themselves be a proxy for earthquake damage and find they cannot. For further discussion of the appropriate use of nightlights, see Gibson *et al.* (2021).

ground acceleration pga:

$$ED_{e,i,r,t} \equiv \sum_{b \in B} s_{b,r,t-1} DR_{b,e,i,r,t}(pga_{e,i,r,t}) \tag{2}$$

where s are the shares of building types (b) within prefecture r at time $t-1$. The weights W in Equation 1 are constructed as:

$$W_{i,r,t-1} \equiv \frac{L_{i,r,t-1}}{\sum_{i \in r} L_{i,r,t-1}} \tag{3}$$

L is the asset exposure at location i in prefecture r at time $t-1$, which we proxy by nightlight intensity.

3.2 Modeling The Determinants of Fiscal Expenditures

We estimate two different regression models. The first model is a fixed effects model which analyzes the effect that earthquake damage has on aggregate real fiscal spending at the local level (excluding grants). This model is similar to the Jerch *et al.* (2020) estimations conducted for hurricanes using US county data. The model is defined as follows:

$$\ln TE_{r,t} = \beta_{ED} ED_{r,t} + \beta_F F + \lambda_t + \theta_r + e_{r,t} \tag{4}$$

where $\ln TE_{r,t}$ is the log of total real expenses[6] for region r in year t, $ED_{r,t}$ is the regional annual damage value from Equation 1 for the same prefecture or town and year, F is a dummy used in the town regressions to signify that the town was impacted by the Fukushima event

[6] All monetary values are deflated to the base year of 2011.

(given its impacts are orders of magnitude larger), λ_t is a vector of year dummies, while θ_r is the prefecture or town fixed effects and $e_{r,t}$ is the error term. To correct for potential heteroskedasticity we use Driscoll-Kraay standard errors.

The second model is run at the budget category level. Given that the data are structured as spatio-temporal panel data, a fixed-effect regression methodology could be used, with the expenditure ratios as the dependent variable and the damage indices as independent variables. However, the different ratios are necessarily related to each other, and thus to take account of this we use the seemingly unrelated regressions (SUR) method with Prais Winsten standard errors of autoregressive order one, as explained in Blackwell *et al.* (2005), and based upon Baltagi (2001), Judge *et al.* (1988) and Wooldridge (2002). It utilizes a system of SUR with error components, where one assumes that all coefficients of constant terms are the same across the system and that all independent variables are quantitative and require restrictions across the panels in their equations, while fixed-effect dummies vary by panel. In our case this translates into a set of equations:

$$B_{j,r,t} = \beta_{ED_j} \cdot ED_{p,t} + \lambda_t + \mu_{j,p} + e_{j,p,t} \tag{5}$$

where the left hand side is defined as the ratio:

$$B_{j,r,t} \equiv \frac{C_{j,p,t}}{\sum_{j \in J} C_{j,p,t}} \tag{6}$$

where C is the expenditure in budget category j, $\mu_{j,p}$ a vector of fixed effects, λ_t a vector of yearly dummy terms, and , $e_{j,p,t}$ the error term.

4 Data

4.1 Fiscal Expenditure

The fiscal expenditure data are taken from the *NikkeiNeeds* data collected by Nikkei Newspaper, Co.[7] The data-set covers, annually, the time period 2007-2014 and contains a detailed breakdown of 14 fiscal spending categories from 47 prefectures and 1,718 municipalities (city, town and village).[8] Due to computational constraints, we aggregated the 14 categories up to the following 6 categories:

- Education
- Public services: Health, Welfare, Labor and Fire/Police (when applicable)
- Construction (public works)
- Public Debt
- Disaster Relief
- Miscellaneous: Carry-over from previous year, Parliament costs, General Administration Costs, Agriculture and Fishery, Commerce, and Manufacturing.

Prefectures and municipalities are responsible for different levels of public services. In principle, the followings are typical task allocations:

- Education: Prefectures are in charge of public high schools, permits for private schools, human resources, and wage payments for teachers in all public junior high and elementary schools. Municipalities are in charge of management of all public junior high

[7]Local Pubic Finance Part in Regional Economy Section.

[8]Before 2007, there was a wave of municipality mergers.

and elementary schools, school lunch meal programs, construction and management of school facilities, and management of public halls and libraries.

- Public services (Health, Welfare, Labor and Fire/Police): Prefectures are in charge of police, public hospitals, and medical services. Municipalities are in charge of fire, garbage disposal, social support programs for children, the elderly, disabled, and low-income people, and the management for pensions, social security, and national insurance.

- Construction: Prefectures are in charge of building and managing national and prefectural roads, major rivers (first-class and second-class rivers), coast, levees, and dams. Municipalities are in charge of small streams, town/community roads, parks, and sewage.

4.2 Earthquake Damages

To model earthquake damage, we utilize four different data sets that provide information on the intensity of the hazard, the vulnerability of the building stock, and population and asset exposed to it in the affected areas. The intensity measures are from the United States Geological Survey's (USGS) ShakeMaps, which are contour maps automatically generated by using data from seismological ground stations. The station values are interpolated to point coordinates which are usually spaced 0.0167 degrees apart (approximately 1,500 meter). Each point includes several different parameters for intensity, such as peak ground acceleration (PGA), peak ground velocity (PGV), and modified Mercalli intensity (MMI).

The vulnerability of the building stock is derived from curves developed in Yamazaki & Murao (2000), where the authors surveyed the damages which buildings sustained during the 1995 Kobe Earthquake. The damage numbers are defined according to 6 building types and the construction period. The 6 building types are wood-frame, wooden-prefabricated, reinforced concrete, steel-frame, light-gauge steel-prefabricated and others.[9] Preferably one would want fragility curves that are localized, if construction standards differ locally. Here, we have assumed homogeneous vulnerability, per construction type, in all localities. The fragility curves are used on national building data, which is categorized into 4 categories: wood and wooden materials, reinforced concrete, steel, and other buildings.[10]

The information about the construction period provided in the data depends on the building material, where for wood they are classified as pre-1970, 1971-1980, 1981-1990, 1991-2000 and post-2000, for concrete and steel the periods are pre-1970, 1971-1980 and post-1980 and for others there are no specific periods. Our source provides annual data (1992-2014) of the percentage share of buildings in each category in each of the 47 prefectures in Japan. Lacking further spatial dis-aggregation in terms of building characteristics, our working assumption is that all towns within a prefecture have an identical composition of the building stock, and that these only differ across prefectures.[11]

Finally, to determine the asset exposure of an area (i.e., how many buildings/assets there are), we use annual nightlight values from the Defense Meteorological Satellite Program (DMSP). The data are gathered via satellite from an altitude of approximately 800km twice every 24 hours. The raw values are fit into 30 arc-second grid-cells and are then averaged to construct an annual mean value, which is normalized, converted to a digital number from 0

[9]The 'others' category contain steel-frame reinforced concrete, light-gauge steel-frame, brick, concrete block, and steel prefabricated.

[10]Data is from the Housing and Land Survey, prepared by the Ministry of Internal Affairs and Communications. We have assumed that wood and wooden materials have similar vulnerability as wood-frame and that steel-frame and steel-prefabricated are the same as steel-frame.

[11]In countries where more detailed information about the building stock is available, it is possible to improve the precision of these calculations of exposure and vulnerability interactions.

to 63, and made publicly available by the U.S.'s National Oceanic and Atmospheric Administration (NOAA). We use the stable, cloud-free series for the years 1992-2013 described in Elvidge *et al.* (1997).[12]

5 Results

5.1 Descriptive Statistics

Table 1 and Table 2 depict the descriptive statistics across total and expenditure categories, and by regional units (Prefectures, All Towns, Big Cities, and Smaller Towns). The top panel in each table shows the number of observations, mean, standard deviation and maximum value of each budget category, whereas the bottom panel provides the same descriptive statistics for total expenditures and earthquake damage. The budget composition between prefectures and towns is seen in the top panels. In percentage terms, prefectures spend on average a much larger share on education (25% vs 11%) and Construction (19% vs 11%), while towns on average spend much more on Public Services (39% vs 19%). When comparing expenditures across the categories, the prefectures' overall spending during this time period is a bit lower than the overall spending at the town/city level; 383 as compared to 403 trillion yen, respectively. Finally, we find that in our data, prefectures experience, on average 0.03% damage, while the corresponding figure for towns is 0.07%. This low average value may not be surprising since earthquakes are a geo-spatially constrained events.

The earthquakes that caused the most damage, according to our damage index, oc-

[12] In this series, intermittent lights such as fishing vessels and fires have been removed, and the final values have been corrected for solar glare and light, moonlight, and clouds.

curred in 2011 in Miyagi prefecture (the Great East Japan Earthquake - GEJE) and in Kariwa in Niigata prefecture in 2007 (Chuetsu offshore quake). The GEJE struck on 11 March 2011 and had a magnitude of 9.0-9.1 M_w. The epicenter was 70 kilometers off the coast of the Tohoku region, and its most devastating damages were caused by a subsequent tsunami, which led to the nuclear meltdown at the Fukushima Daiichi Nuclear Power Plant. Overall, the earthquake and tsunami led to 18,426 casualties (confirmed dead and missing), almost 1 million damaged buildings and total economic costs in excess of USD 300 billion. In April 2011, the 7.1 M_w Miyagi earthquake occurred approximately 66 kilometers off the coast of Honshu. It was the strongest of the aftershocks following the GEJE catastrophe, and while there were no reported structural damages, our model will have calculated some minor damages making the aggregated damage for 2011 the highest in Miyagi prefecture.[13]

[13] Since our modelled damage is based on shakemaps, it greatly under-estimates the damage from the GEJE, as these damages were mostly associated with the tsunami (which we do not model). We therefore also conduct our estimates excluding this outlier GEJE event. Other than the GEJE, the 2007 Chuetsu offshore quake was the most damaging earthquake as modeled by the damage index we use here. The highest impact we identify using our algorithm was in Kariwa in Niigata prefecture, which corresponds to the post-earthquake damage reports. In total the earthquake caused 11 deaths, more than 1,000 injured and the complete destruction of 342 buildings.

Table 1: Descriptives of Variables for Prefectures and All Towns

	Prefecture				All Towns			
Category	Obs	Mean	Std. Dev.	Max	Obs	Mean	Std. Dev.	Max
Education	376	0.253	0.07	0.47	13,736	0.11	0.042	0.493
Public Services	376	0.194	0.062	0.473	13,736	0.391	0.096	0.798
Construction	376	0.18	0.064	0.348	13,736	0.109	0.046	0.723
Public Debt	376	0.111	0.059	0.307	13,736	0.125	0.046	0.401
Disaster relief	376	0.013	0.017	0.212	13,736	0.007	0.02	0.379
Miscellaneous	376	0.249	0.072	0.492	13,736	0.253	0.091	0.943
Total Expenditures (2011 base year. M Yen)	376	1,005,709	859,561	7,095,188	13,736	29,372	108,365	3,423,397
Earthquake damage (% multiplied by 100)	109	0.034	0.183	1.819	1,858	0.071	0.446	10.39

Notes: The top panel shows the mean percentage shares, standard deviations and maximum shares of the 6 budget categories across prefectures and all towns. The bottom panel shows the same descriptives across the same categories for total expenditures expressed as million Yen rebased to 2011 and earthquake damage expressed as a percent of building damage

Table 2: Descriptives of Variables for 59 Big Cities and Rest of Towns

	59 Big Cities				Rest of Towns			
Category	Obs	Mean	Std. Dev.	Max	Obs	Mean	Std. Dev.	Max
Education	472	0.098	0.025	0.183	13,264	0.111	0.043	0.493
Public Services	472	0.454	0.092	0.631	13,264	0.388	0.095	0.798
Construction	472	0.138	0.042	0.274	13,264	0.107	0.046	0.723
Public Debt	472	0.12	0.033	0.216	13,264	0.125	0.047	0.401
Disaster relief	472	0.002	0.008	0.108	13,264	0.008	0.021	0.379
Miscellaneous	472	0.164	0.049	0.384	13,264	0.256	0.09	0.943
Total Expenditures (2011 base year. M Yen)	472	292,382	308,219	1,708,008	13,264	20,013	78,981	3,423,397
Earthquake damage (% multiplied by 100)	71	0.042	0.156	1.047	1787	0.072	0.453	10.39

Notes: The top panel shows the mean percentage shares, standard deviations and maximum shares of the 6 budget categories across 59 large cities and the remaining towns. The bottom panel shows the same descriptives across the same categories for total expenditures expressed as million Yen rebased to 2011 and earthquake damage expressed as a percent of building damage

5.2 Regression Results

The results from the sets of level-of-spending regressions using the model in Equation 4 are seen in Table 3. Each coefficient estimate represents a separate regression with the provided coefficient (and its accompanying standard error) describing the association of the earthquake damage variable with the budget category noted on the left. Thus, column (1) represents estimates from 6 separate regressions; for each of the 6 budget categories, and for total fiscal spending. For example, the coefficient on the upper left (1.762) references the impact of earthquake damage on spending on education at the prefecture level.

The results show that in the prefecture sample, earthquake damage is associated with more disaster relief, and consequently with higher total expenditure, but does not seem to affect any of the other spending categories. Column (3) replicates the prefecture regressions, but at the smaller administrative level. Indeed, the results obtained from the prefecture sample seems to hold. Even when examining spending at the lower administrative level, most of the increased spending that is statistically observable is for disaster relief (and miscellaneous spending). However, once we split the sample into the largest administrative units within that sample (the 59 biggest cities) in column (4), and the smaller towns in columns (5), we observe that the main fiscal impact of the earthquake events is observed for the bigger cities. For these, we observe increases in spending for all the budget categories, with the largest increase still observable in the disaster relief effort. We note that all of these regressions implicitly control for all national business cycle effects (with year dummies) and for the 3/11/2011 GEJE (since it is clearly an outlier).

Next, in Table 4, we investigate whether the earthquake is also associated with a delayed effect on the budget, in the following year. We see only weaker evidence for this. In almost all cases, the contemporaneous effect on total expenditure is statistically significant, but the lagged effect is significant only for the smaller town sample (and consequently also for the full 'all towns' sample).

Table 3: Expenditure Regressions for Budget Categories

Budget Category	Prefecture		All Towns & Cities	59 Cities	Smaller Towns
	(1)	(2)	(3)	(4)	(5)
Education	1.762	8.795	8.067	61.603***	9.26
	(4.51)	(7.212)	(5.825)	(0.214)	(5.511)
Public Services	37.766	44.578	16	95.11***	17.199
	(31.146)	(28.723)	(7.715)	(0.158)	(7.332)
Construction	-20.51	-25.252	5.184	76.284***	6.514
	(25.158)	(24.59)	(6.271)	(0.351)	(5.866)
Public Debt	34.506	41.01	1.555	113.071***	2.587
	(18.801)	(21.985)	(8.557)	(0.17)	(8.144)
Disaster relief	174.846***	173.392***	60.519***	483.961***	59.835***
	(10.872)	(8.646)	(2.674)	(0.657)	(2.274)
Miscellaneous	2.473	5.972	13.719**	186.571***	14.39***
	(6.663)	(5.603)	(4.478)	(0.163)	(3.888)
Observations	376	376	13,658	461	13,197
Includes Year Dummies	Yes	No	Yes	Yes	Yes
Includes Fukushima Dummy	No	No	Yes	Yes	Yes

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
Each coefficient represents β_{ED} estimates for 6 budget categories from the model $\ln TE_{r,t} = \beta_{ED} ED_{r,t} + \beta_F F + \lambda_t + \theta_r + e_{r,t}$ (Equation 4).
The model is run across 4 different administrative levels: prefecture, all towns, 59 large cities and the remaining towns. Fukushima and year dummies are included when noted in the bottom panel.

Table 4: Total Expenditure Regressions

Total Expenses	Prefecture			All Towns & Cities		59 Cities		Smaller Towns	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year of Earthquake	17.956**	21.228***	22.872***	4.936***	6.832**	13.106	15.816	4.915***	6.778**
	(6.168)	(5.493)	(5.608)	(0.763)	(2.427)	(10.354)	(11.28)	(0.729)	(2.353)
Year after EQ			4.584		8.837**		31.257		8.745**
			(6.178)		(3.537)		(12.989)		(3.494)
Observations	376	376	329	13,662	11,983	461	407	13,201	11,576
Includes Year Dummies	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Includes Fukushima Dummy	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
Each coefficient represents β_{ED} estimates for total expenditures from the model $\ln TE_{r,t} = \beta_{ED} ED_{r,t} + \beta_F F + \lambda_t + \theta_r + e_{r,t}$ (Equation 4). The model is run across 4 different administrative levels: prefecture, all towns, 59 large cities and the remaining towns. Fukushima and year dummies are included when noted in the bottom panel. In addition, columns (3), (5), (7) and (9) include a lagged coefficient estimate of β_{ED} at time $t + 1$.

Table 5: Increase in Cost following an Earthquake (M Yen and % change)

Assumed EQ impact	Prefecture	All Towns	59 Cities	Smaller Towns
	(1)	(2)	(3)	(4)
Mean	6,241 (0.6)	103 (0.4)	1,624 (0.6)	71 (0.4)
Max	388,436 (38.6)	19,687 (67.0)	42,996 (14.7)	13,341 (66.7)

Notes: Estimated total cost increases in million yen when using the coefficients from Table 4 to quantify the impact on total expenditures following a mean and maximum strength earthquake during the time period. The values inside brackets are percentage change in total expenditures.

The calculated total fiscal expenditure we can expect, after an earthquake event, given past experience, is provided in Table 5, focusing on the mean earthquake and on the most damaging earthquake in our sample hitting the 'average' prefecture and town. In other words, we calculate the assumed shift in expenditure following an earthquake with mean or maximum damage values. As can be expected, the numbers are highest if we examine the fiscal accounts of prefectures or large cities, and are much higher for the most damaging earthquake than for the average one. The numbers in parentheses denote the percentage change in the fiscal spending, by category, that is associated with an average earthquake, and the largest one. We note that the increase in spending is very small for an average event, but a large event entails a potentially very large increase in spending. In the most extreme case, for small towns, a large event (in our sample, since we exclude the GEJE, this is still not a very large catastrophe) entails an increase in spending of 67 percent.

The final set of regression results are shown in Table 6 and estimate the impact of the earthquake shocks on the budget shares for each category as share in the total budget as a SURE model, as described in Equation 5. Given what we have observed in Table 3, it is not surprising that the share of public spending on disaster relief increases significantly at the prefecture level, with no corresponding change in the other budget lines. At the lower administrative units (columns 3-5), however, there is a decrease in the share of spending going to finance other priorities. For the bigger cities (column 4) we observe a decrease in the share of spending targeting education, while for the smaller towns we see that spending on construction and on public debt has gone down, accompanied by an increase in spending on public services.

Why does spending on other items (other than direct disaster relief) go down in municipalities, and especially in the bigger cities, but not at the prefecture level? First, public services and administrative tasks are allocated between prefectures and municipalities. Although some tasks are shared by both, prefectures tend to be in charge of high-value and geographically-broad-based tasks and municipalities tend to be in charge of services that are closer to daily life and the public services they depend on. Second, since municipalities are located on the 'post-disaster frontier,' they end up responding to the many unexpected issues that plague recoveries. As such, they need to readjust budgets more, and potentially reduce spending in some categories. Third, the total budget in municipalities is much smaller than in prefectures. Thus, the composition of spending is more likely to be affected from large negative shocks.

Furthermore, we observe some differences in spending patterns after disasters between larger and smaller municipalities. The share of educational spending in the bigger cities accounts for around 20 percent, but only around 10 percent for the smaller municipalities. Bigger cities can therefore reduce educational cost more easily. In terms of public debt, in case of natural disasters, the redemption period of public debt by municipalities can be postponed as special treatment. Thus smaller cities tend to postpone it, which will reduce the immediate expenditure on public debt servicing. In addition, in case of disasters, bonds can be issued specifically for recovery and reconstruction under better terms than during more 'normal' times. Municipalities can issue bonds to finance reconstruction, and this can reduce their usual debt spending.

Table 6: Regression results for Prefectures and All Towns

Budget Category	Prefecture		All Towns & Cities	59 Cities	Smaller Towns
	(1)	(2)	(3)	(4)	(5)
Education	-4.65	-3.68	-0.209	-2.415***	-0.197
	(3.403)	(3.46)	(0.155)	(0.799)	(0.153)
Public Services	2.329	2.867	1.921***	-0.751	1.924***
	(6.065)	(6.035)	(0.465)	(2.564)	(0.459)
Construction	0.474	-0.741	-1.131***	-5.314	-1.114***
	(3.082)	(2.74)	(0.315)	(2.998)	(0.307)
Public Debt	-1.12	-0.659	-0.527***	-1.704	-0.525***
	(2.039)	(2.115)	(0.092)	(1.166)	(0.09)
Disaster relief	6.111***	5.977***	0.916***	6.644***	0.889***
	(0.256)	(0.261)	(0.174)	(1.542)	(0.174)
Miscellaneous	-4.511	-4.18	-0.93	2.939	-0.949
	(5.424)	(5.43)	(0.515)	(3.948)	(0.504)
Observations	2,256	2,256	82,416	2,832	79,584
Includes Year Dummies	Yes	No	Yes	Yes	Yes
Includes Fukushima Dummy	No	No	Yes	Yes	Yes

Notes:
***Significant at the 1 percent level.
**Significant at the 5 percent level.
Each coefficient value represents β_{ED} estimates for 6 budget categories in a system of seemingly unrelated regressions (SUR). The estimated model is $B_{j,r,t} = \beta_{ED_j} \cdot ED_{p,t} + \lambda_t + \mu_{j,p} + e_{j,p,t}$ (Equation 5).
The coefficient values represent a change in the share of the total budget. The model is run across 4 different administrative levels: prefecture, all towns, 59 large cities and the remaining towns. Fukushima and year dummies are included when noted in the bottom panel.

6 Conclusion

Disasters have myriad consequences, not least of which is their impact on the government's accounts. Previous papers have typically examined the aggregate amount of fiscal spending one can expect after a disaster event. These generally concluded that: the government accounts deteriorate in a disaster's aftermath; spending increases and tax revenue declines, debt increases, and the likelihood of a sovereign rating downgrade or even default increases. In this paper we focus on Japan and investigate what happens to public spending and its decomposition in prefectures and towns after earthquake disasters. More specifically, Japan is the country most exposed to earthquake disaster risk globally and we use its past earthquake experience together with detailed (by budget line) fiscal data for the past decade. Importantly, in Japan each administrative level (prefectures and municipalities) is responsible for a different set of public services. After a disaster, the central government deploys various financial arrangements and subsidies with the local governments, in order to ensure the continuing provision of public services. In particular, for large-scale disasters, a special law specifies that the central government is required to provide special subsidies and special treatments to local governments. Arguably one should not expect a large pro-cyclical decline in spending as was previously observed post-disaster in low-income countries.

We find that the share of public spending on disaster relief, at the prefecture level, increases significantly, but with no corresponding change in the other budget lines. In contrast, at the lower administrative units, we do observe a decrease in the share of spending going to finance other priorities. For the bigger cities, we observe a decrease in the share of spending targeting education, while for the smaller towns we see that spending on construction and on public debt has gone down, accompanied by an increase in spending on public services.

The evidence we present suggests that while, at the prefecture level, fiscal policy-making is robust enough to prevent presumably unwanted declines in spending on public services because of a disaster, the same cannot be said for the city/town level. There it seems that the fiscal allocation system in Japan is still not robust enough to prevent these decreases. Since we find that these are only short term declines in some spending categories, the question of the likely longer-term impact of these declines in spending remains open. For example, would the decrease in spending on education culminate in lower educational achievement in the affected locality? Remarkably, while there is an international literature that documents decline in educational attainment post-disaster in low- and middle-income countries, there is little that connects any observed declines in educational attainment with reduced public spending on education (e.g., Gitter & Barham (2007) and Rush (2018)). We leave these questions for future research.

7 Figures

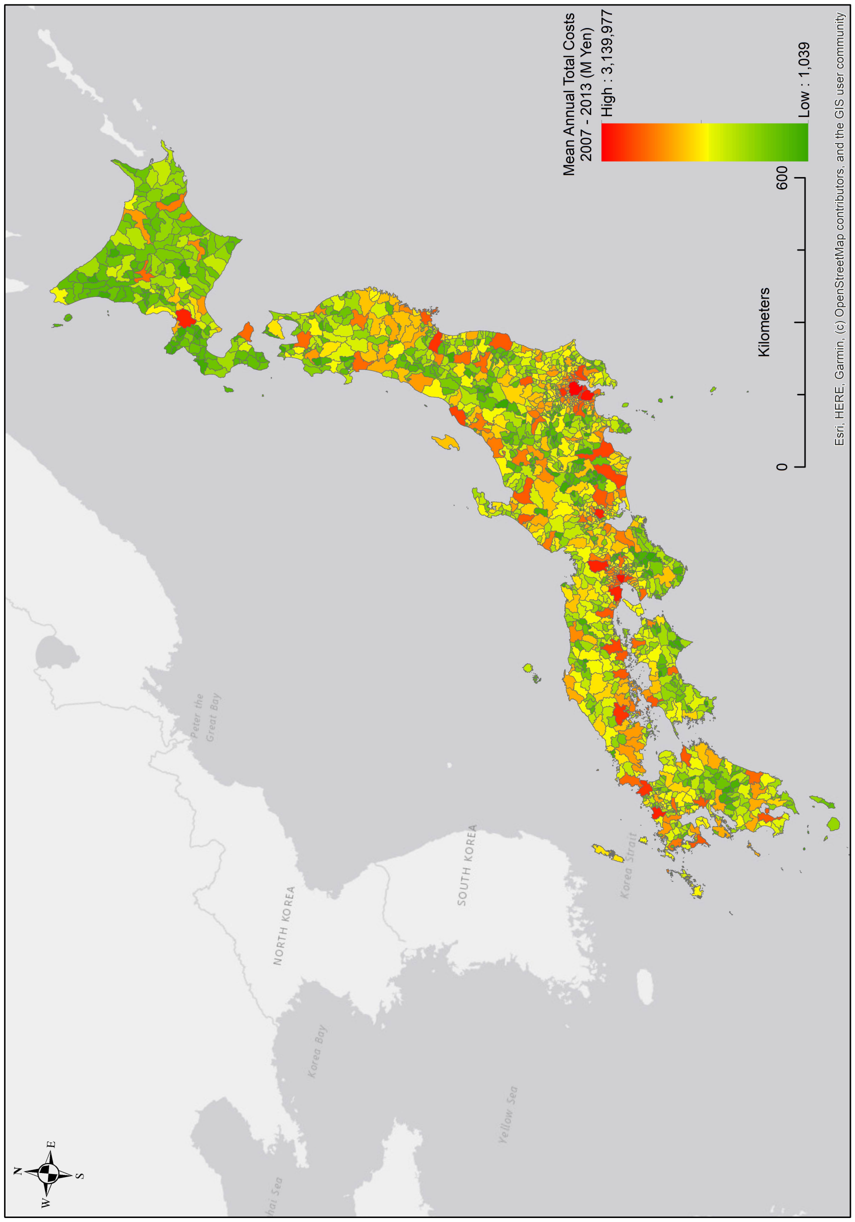

Figure 1: Mean Annual Total Costs by Town (Million Yen. Red is higher)

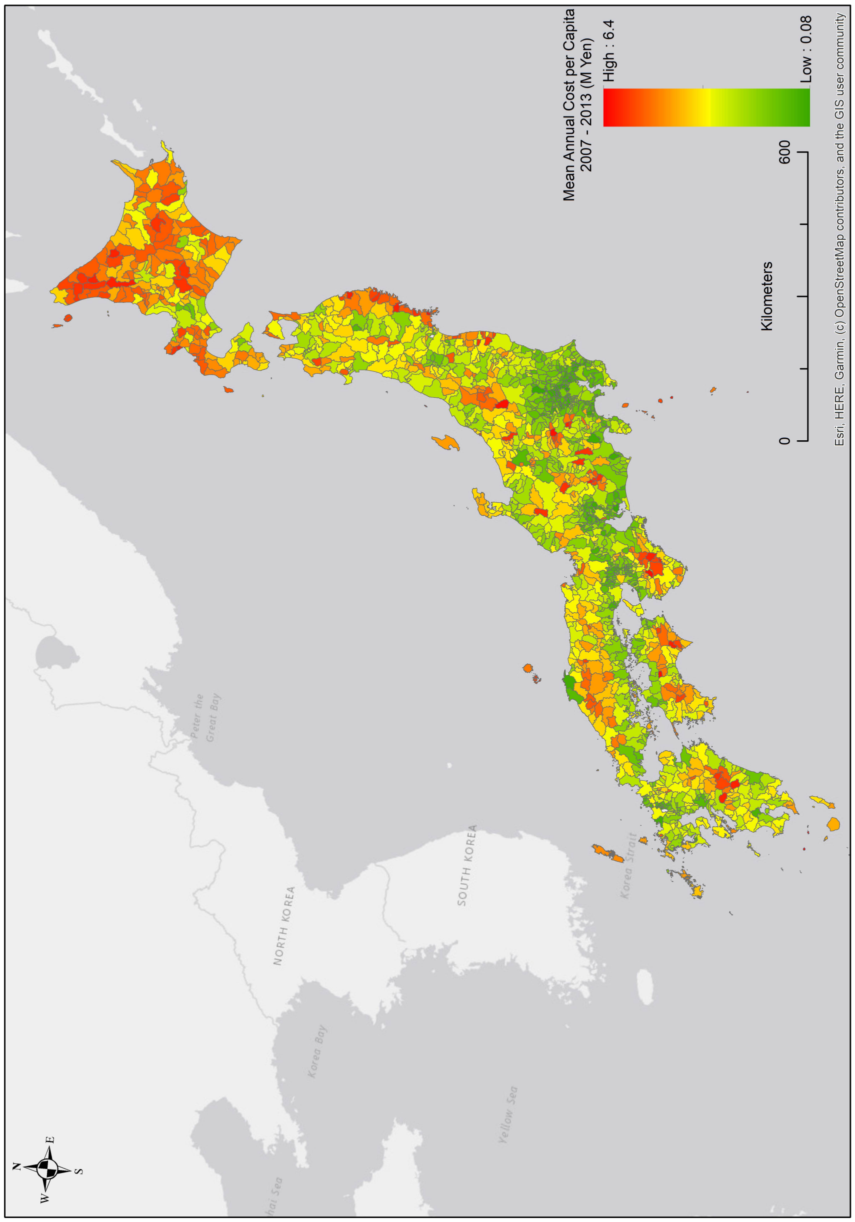

Figure 2: Mean Annual Cost per Capita by Town (Million Yen. Red is higher)

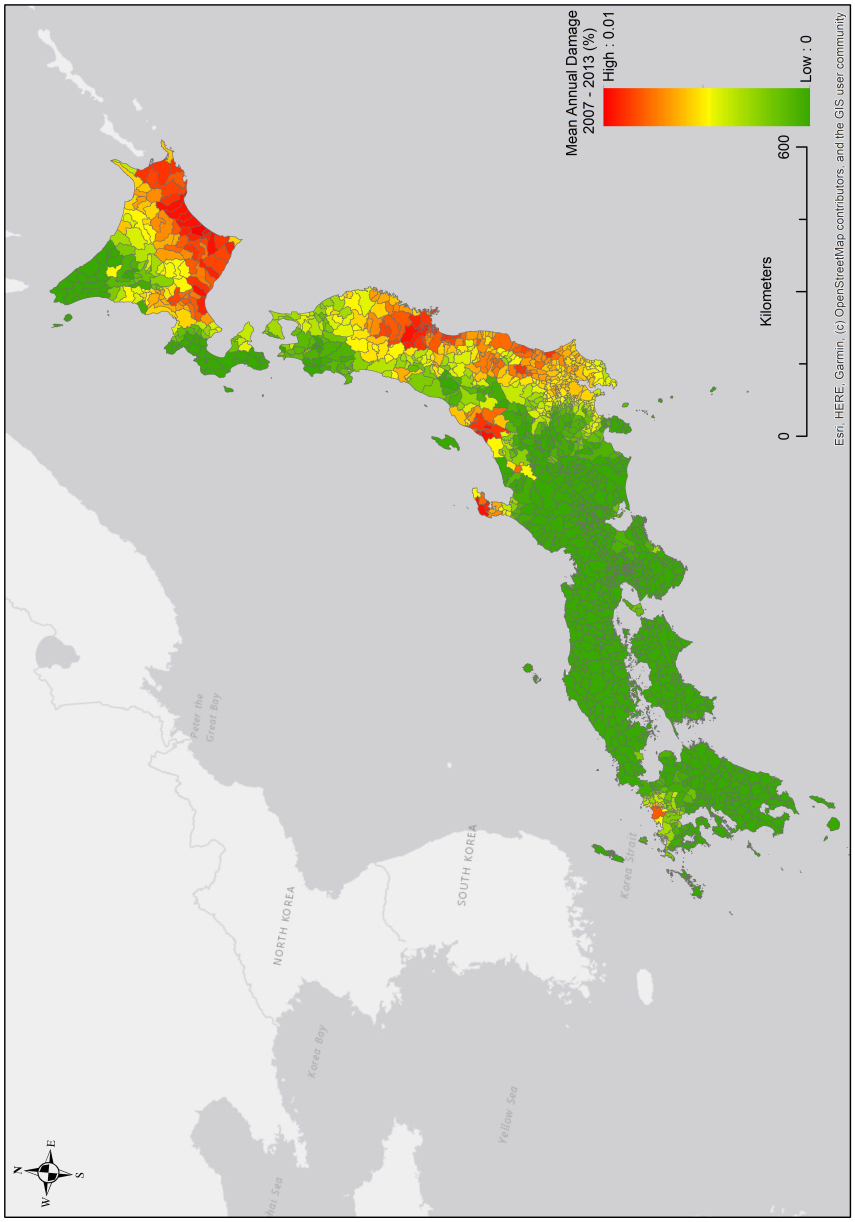

Figure 3: Mean Annual Earthquake Damage by Town (Red is higher)

A Appendix - all 14 budget categories for prefectures

Table 7: Descriptives of Variables for Prefectures and All Towns

	Prefecture			
Category	Obs	Mean	Std. Dev.	Max
Administration Costs	376	0.009	0.005	0.047
Agriculture and Fishery	376	0.482	0.345	2.524
Commerce	376	0.003	0.02	0.22
Construction	376	0.292	0.187	1.569
Disaster Relief	376	0.038	0.046	0.566
Education	376	0.344	0.154	0.875
Firefighting	376	0.234	0.11	0.63
Health	376	0.299	0.271	2.91
Labor	376	1.08	0.548	3.814
Parliament	376	0.15	0.091	0.613
Police	376	0.787	0.466	3.217
Public Debt	376	0.411	0.176	0.813
Welfare	376	0.057	0.09	1.205
Miscellaneous	376	0.002	0.013	0.213
Earthquake damage	109	0	0.002	0.018
Total costs (2011 base year. M Yen)	376	1020502	866406.6	7216703

Table 8: Regression results for Prefectures and All Towns

Budget Category	With year dummy	No Year Dummy
	(1)	(2)
Administration Costs	-0.031	0.085
	(1.619)	(1.526)
Agriculture and Fishery	-1.862	-1.438
	(1.724)	(1.854)
Commerce	-3.619	-4.261
	(5.372)	(5.51)
Construction	0.474	-0.741
	(3.082)	(2.74)
Disaster Relief	6.111***	5.977***
	(0.256)	(0.261)
Education	-4.65	-3.68
	(3.403)	(3.46)
Firefighting	-0.004	0.012
	(0.006)	(0.025)
Health	0.364	0.595
	(0.363)	(0.373)
Labor	4.752***	4.716***
	(0.993)	(0.952)
Parliament	-0.055	-0.048
	(0.03)	(0.025)
Police	0.298	0.311
	(1.144)	(1.062)
Public Debt	-1.12	-0.659
	(2.039)	(2.115)
Welfare	-3.285	-3.019
	(6.621)	(6.513)
Miscellaneous	0.011	0.001
	(0.014)	(0.032)

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
Each column presents a system of regressions

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