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The physical and social determinants of mortality in the 3.11 tsunami

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ABSTRACT

The human consequences of the 3.11 tsunami were not distributed equally across the municipalities of the Tohoku region of northeastern Japan. Instead, the mortality rate from the massive waves varied tremendously from zero to ten percent of the local residential population. What accounts for this variation remains a critical question for researchers and policy makers alike. This paper uses a new, *sui generis* data set including all villages, towns, and cities on the Pacific Ocean side of the Tohoku region to untangle the factors connected to mortality during the disaster. With data on demographic, geophysical, infrastructure, social capital, and political conditions for 133 municipalities, we find that tsunami height, stocks of social capital, and level of political support for the long-ruling LDP strongly influenced mortality rates. Given the high probability of future large scale catastrophes, these findings have important policy implications for disaster mitigation policies in Japan and abroad.

1. Introduction: the puzzle

The 9.0 magnitude earthquake offshore Japan's northeast coast on 11 March 2011 at 2:46 p.m. itself caused relatively little damage to the residents and buildings in the northeast region of Japan known as Tohoku. Estimates put the death rate from the earthquake at less than five percent of overall fatalities (see National Police Agency of Japan, (2014)). However, the massive thrust-fault set off multiple tsunami with a maximum height of more than 20 m (65 feet) which devastated coastal communities and shut down the cooling systems and backup generators at the Fukushima Dai-ichi nuclear power plant. This paper focuses on the single Japanese administrative layer known as *shi cho son*, literally city, town, and village. Throughout in this paper, we follow the Japanese designation for this level of analysis and use the labels municipality, city, town, and village interchangeably.

The emotional and political impact of the compounded disaster reached well beyond Japan's shores; the fuel meltdowns altered the energy frameworks for several European nations (including Germany, Italy, and Belgium) and forced the United States' Nuclear Regulatory Commission to rethink its regulations (Aldrich, 2011b). In Japan, the tsunami killed more than 15,800 people, caused the disappearance of an additional 2600 and forced the evacuation of some 400,000 residents (National Police Agency of Japan, (2014)). Yet, mortality rates from the tsunami varied tremendously across Japanese municipalities, many of which were not located directly on the coast. This paper focuses solely on deaths caused directly by the tsunami through drowning or crush injuries. While data is available on the post-tsunami deaths from factors such as exposure, hypothermia, infection, and stress, this paper excludes such post-tsunami outcomes.

The tsunami traveled as far as 15 km inland in some locations (usually moving along a river) affecting coastal and inland cities alike with a typical inundation spread of 4–6 km (Løvholt et al., 2012). The mean proportion of the population missing or deceased in the inundated areas of the locality following the tsunami was 0.01, that is, some 1 in 100 residents with a number of municipalities experiencing no casualties. However, the maximum was 0.11, that is, some 11 percent of the local population, which occurred in the city of Onagawa where more than 600 people perished. Fig. 1 below lays out the tremendous skew in the distribution of mortality across these municipalities; the vast majority of villages, towns, and cities in the Tohoku region suffered no fatalities. The next cluster falls between one and nine percent, and then the highest sits at eleven percent.

An initial bivariate analysis of the height of the tsunami and mortality outcomes for 133 coastal and non-coastal municipalities located in Iwate, Miyagi, and Fukushima prefectures illuminated a visible if weak connection. We graph the height of the tsunami against the mortality rate in each of these cities, labeling each point

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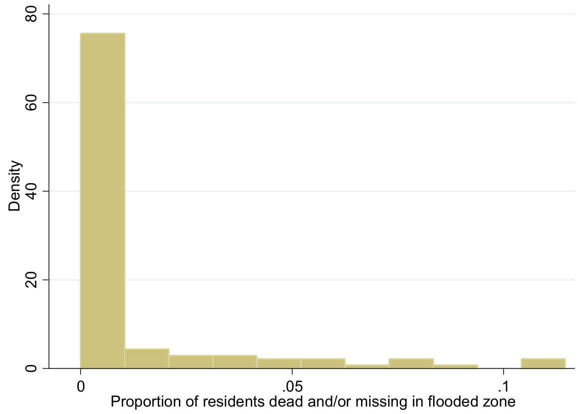


Note: The horizontal axis of the histogram captures the proportion of residents dead or missing in each municipality

Fig. 1. Large variation in mortality outcomes across communities.

with the municipality name. As Fig. 2 below illustrates, the general pattern involves areas struck by higher waves experiencing higher levels of mortality; higher waves created higher risks of death for residents.

However, the pattern is far from perfect. Some cities – such as Tanohata and Miyako – with comparatively high tsunami heights (greater than 19 m, roughly 60 feet) had far lower mortality rates. In other cities with relatively short tsunami (fewer than 7 m, roughly 21 feet) – such as Higashimatsushima and Yamamoto – the death toll was disproportionately higher. This variation in mortality rates – which does not vary exclusively with the strength of the tsunami – remains a critical puzzle for researchers to understand.

This article analyzes a new, *sui generis* dataset of all Tohoku municipalities to uncover physical and social determinants of mortality in the 3.11 tsunami. Envisioning the tsunami as a "large, highly variable, clearly identifiable, and purely temporary" exogenous shock (Davis and Weinstein, 2002: 1277), this paper seeks to understood how local environmental and social conditions affected disaster mortality (Miguel and Roland (2011) follow a similar identification strategy). Our analysis demonstrates that along with tsunami height and political support for the Liberal Democratic Party (LDP, Jimintō), the strength of pre-tsunami bonding social capital strongly influenced the proportion of local residents living in inundated areas killed by the tsunami. More than demographic factors or the height of local tsunami walls, political connections and the depth of social ties influenced the rates of death during the disaster.

We believe that this paper makes several contributions to the literature. First, to our knowledge, it is the first English language

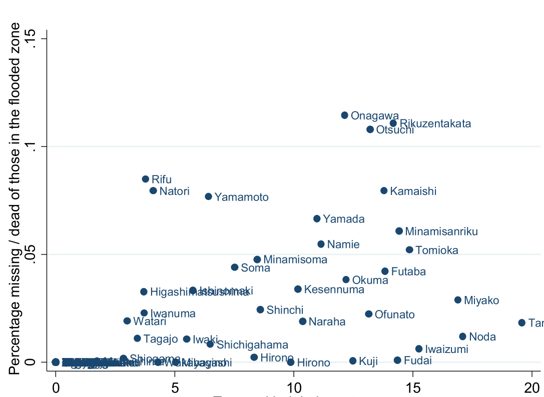


Fig. 2. Tsunami height correlation with mortality.

paper to quantitatively analyze mortality from the 3.11 disaster in Japan across the entire set of municipalities in the Tohoku region. It joins a handful of other papers which have moved beyond qualitative analysis and small samples to establish new baseline parameters for factors responsible for disaster-related deaths (Nishikiori et al., 2006; Guha-Sapir et al., 2006). Next, it advances beyond standard demographic explanations for disaster deaths by incorporating relatively unexplored explanations including local reserves of social capital (cf. Klinenberg, 2002). Where other articles on crisis mortality have remained focused on issues of demography and disaster characteristics (Jonkman et al., 2008), this paper builds on recent empirical research cognizant of the role of social cohesion and networks in crises (Kage, 2011; Aldrich, 2012). Our focus on the role of social capital is important as it challenges previous research which found little evidence for protective effects from social networks during disaster (Browning et al., 2006). This paper brings strong evidence that strong social ties provided benefits during the disaster itself.

Finally, this paper brings with it clear policy implications for disaster mitigation and hazard reduction which suggest that a number of ongoing public policies may either be ineffective or even moral hazards. For example, while Japanese authorities continue to expend vast sums of money to restore damaged seawalls and construct new ones in the Tohoku region and elsewhere (*Japan Times* 16 April 2014), we find no evidence which is consistent with a hypothesis that such levees had any measurable impact on mortality rates. Further, given that our data illuminate the critical role of pre-disaster social cohesion in reducing vulnerability to crises, we suggest that authorities re-orient spending away from solely strengthening physical infrastructure to enhancing social infrastructure.

2. Determinants of mortality

Past research has identified a number of factors which may strongly influence post-disaster mortality (Kahn, 2005). These include disaster and local environmental characteristics, demographic factors, the capacity of local social networks, and political as well as economic factors. It is intuitive that the *physical strength of tsunami* – that is, its height and speed upon reaching shore – strongly influenced mortality among affected communities. The chances of individual survival hinge critically on proximity to the ocean in combination with the water's path and geophysical land features (Frankenberg et al., 2011). Disaster experts regularly connect the amount of damage done by a disaster like a tsunami or earthquake to survival and recovery rates (Dacy and Kunreuther, 1969; Haas et al., 1977). Hence many would assume the higher the tsunami at its peak as it approached a community, the greater the mortality. Along with the height of the tsunami itself, a number of geographic conditions may determine the actual impact of the wave when it reaches the shore. These *geographic conditions* include the coastal length of the municipality, its area, and the length of paved roads. The coastal length of the town, village, or city may determine its broader exposure to the wave itself; longer coastlines may create more victims than areas with a narrower set of beaches. Similarly, municipalities with larger area may have more citizens vulnerable to the wave or they may have easier escape paths from low lying areas; the effect of these geographical features remains indeterminate. The length of paved roads provides a measure of the escape paths available to citizens fleeing from the disaster; such roads serve as the most likely out migration routes. Finally, we include a measure of the local population engaged in the fishing industry recognizing that the more people who were working in the coastline area the higher the mortality rate could be.

While the physical characteristics of the disaster event and the locations of potential victims may influence mortality, a great deal of work has focused on the role of *demography* in disaster situations, as characteristics such as age of the affected population strongly correlate with the individual capacity to evacuate and survive a disaster (Guha-Sapir et al., 2006; Nishikiori et al., 2006). We include a measure of the proportion of single person households in each municipality; this variable captures the availability of immediate assistance to the vulnerable. In their study of mortality and the 2004 Indian Ocean tsunami, Frankenberg et al. (2011) found that physical strength strongly predicted survival, with children and older adults least likely to survive the disaster, a finding that is confirmed by another study by Rofi et al. (2006). In the case of the Tohoku region, many of the municipalities had large populations of elderly residents, and their inability to flee along with their relative physical vulnerability may have increased mortality rates. To capture the presence of elderly community members we include a baseline measure of pre-tsunami mortality (which correlates very highly – 0.91 – with the proportion of the village above the age of 65). Including a measure of pre-mortality rate provides an instrument to capture demography which avoids strong correlation with other factors of interest such as LDP support.

Unlike the Indian Ocean tsunami where the earthquake and the retreating ocean water were not uniformly interpreted as a sign of tsunami danger (or acted upon by residents), communities in Tohoku have been repeatedly exposed to tsunami or tsunami training in the past. After an initial earthquake residents in Japan have been trained to expect the arrival of a tsunami; children regularly take part in school-level group evacuation drills and a number of neighborhoods and towns practice communal evacuation as well. Furthermore, some towns and villages such as Aneyoshi and Miyatojima and institutionalized collective memories of past tsunami (some which took place 1000 years ago) through physical markers such as stones (Fackler, 2011; Holguin-Veras, 2012).

As a result, the degree of community organization in the evacuation procedures may have played a powerful role in determining survival rate. Whether or not residents in Tohoku and elsewhere actually leave a tsunami-vulnerable area to flee to higher ground depends not primarily on education, then, but rather on local norms and the behavior of one's family and geographically-defined social network. Accordingly, a different approach to post-disaster mortality focuses on the ability of the community to self-organize and evacuate under extreme conditions. Successful risk avoidance involves accurately receiving, interpreting, and passing along messages about hazards sent out by authorities and providing shared norms-based mutual support for evacuation (Elinder and Erixson, 2012). Social networks in local communities can be seen as a form of pre-existing informal insurance mechanism (cf. Beggs et al., 1996; Sawada and Shimizutani, 2007). Where communities share norms and have deep reservoirs of trust in each other and authorities, they are more likely to act on group information about risks. Therefore pre-disaster levels of *bonding capital* – the ties that bind residents to friends and neighbors – may matter because of their influence on information sharing, mutual help, and collective action.

Localities with the ability to overcome collective action could better facilitate evacuation of the elderly and infirm; fragmented communities with less trust and less ability to work collectively may not been able to do so. As one study of the 1995 Chicago heat wave deaths argued, “those at risk were isolated and lacked a concerned network of family and friends” (NOAA, 1995: 27; see also Klinenberg, 2002). Linking social capital – the ability to connect quickly to decision makers and authorities to verify hazard warnings and to guide rescue efforts – may also have played a role in saving lives. Linking social capital ties strongly into political variables, as we explain below.

In order to test the roles of social capital in tsunami survival, we employ proxies that capture bonding (and linking) social capital in Tohoku localities. We envision pre-tsunami proportional crime rates as a proxy for bonding social capital based on extensive sociological research (Akcomak and Weel, 2008; Buonanno et al., 2009; Ramseyer, 2014). Communities with fewer connections between individuals and lower expectations about future interactions will encounter higher rates of crime than areas where neighbors feel tied to both each other and their homes (Newman, 1996). In regions where people lack past connections or envision themselves as outsiders, they are less likely to abide by local behavioral norms or worry about long term social consequences for deviance (Deller and Deller, 2010). Putnam (2000: 308) argued that “[h]igher levels of social capital, all else being equal, translate into lower levels of crime … This inverse relationship is astonishingly strong—as close to perfect as one might find between any two social phenomena.”

In contrast to solely social connections, some experts on Japan have emphasized that *political factors* – such as local support for the long dominant Liberal Democratic Party and whether or not the municipality was merged with another locality – may affect mortality. This can be expected because stronger support for the LDP may increase subsidies to local governments (Saito, 2010); that money in turn may allow local government officials to increase the number of disaster preparation measures. Towns supportive or at least cooperative with the LDP may have received greater public investments in and experienced better availability of reliable infrastructure, such as sea walls, for tsunami protection (Kerr, 2002). The LDP itself may reward strongly supportive towns differently than those which have opposed it or only weakly supported it in past elections. That is, the LDP may provide fewer benefits to towns which have supported opposition parties yet larger benefits to communities which could “swing” towards the LDP. We use a categorical measure of LDP support to capture potential benefits to swing-voting municipalities.

Szreter and Woolcock (2004: 655) describe a type of connection which they label *linking social capital* as composed of “norms of respect and networks of trusting relationships between people who are interacting across explicit, formal or institutionalized power or authority gradients in society.” Ties between municipalities and Japan's administrative center through party connections can be seen as a form of linking social capital. To incorporate measures of linking social capital and to capture the potential effect of these political decisions on mortality, we included several dummy variables capturing the proportion of LDP party support in 2009 Lower House election. We see this measure of electoral support for the LDP as a strong test of our hypotheses, as the LDP itself lost the 2009 election to the well-organized Democratic Party of Japan (DPJ). Communities in our sample strongly supporting the LDP displayed very strong loyalty to the party at a time when many of their fellow citizens supported the opposition.

We used dummy variables to capture potential nonlinear relationships between LDP support and tsunami mortality; we split the support levels into less than 25%, vote share for the LDP, 25–30% share, 30–35%, and above 35% vote share. This also reduces potential multicollinearity in the final models. We centered these categories around the interval of 25–30% vote share because it was the most common situation in these municipalities (some fifty percent of Tohoku municipalities display this level of support); the other categories were less frequent.

Another political condition may increase a municipality's survival rate during a catastrophe. Since the 1999 Law to Promote Municipal Mergers went into effect in Japan, the number of towns,

Table 1
Descriptive statistics of overall dataset.

Variable (city/town/village level)	N	Mean	Standard deviation	Min	Max
Mortality					
Proportion of dead/missing from inundated area	132	0.010	0.024	0.000	0.115
Geographic/tsunami characteristics					
Tsunami height (meters)	132	2.760	5.031	0.000	19.592
Area of the municipality (square km)	132	275.359	277.787	13.270	1259.890
Sea wall height (meters)	132	2.086	3.835	0.000	15.500
Coast line length (km)	132	4.505	10.281	0.000	64.870
Length of paved roads	127	104.102	104.113	11.000	649.000
Demographic factors					
Population density (people/sq km)	132	287.030	563.064	1.629	3278.365
Pre-tsunami mortality rate	132	0.013	0.004	0.005	0.026
Percentage of population in fishing industry	132	0.0014	0.0039512	0	0.025157
Percentage single-person households	132	0.219	0.068	0.109	0.533
Social capital proxies					
Crimes per 1000 residents	132	0.007	0.003	0.000	0.016
Political factors					
Below 25% LDP support in 2009 LH election (default)	134	0.224	n/a	0	1
25 to 30% LDP support in 2009 LH election	134	0.507	n/a	0	1
30 to 35% LDP support in 2009 LH election	134	0.194	n/a	0	1
Above 35% LDP support in 2009 LH election	134	0.0746	n/a	0	1
Merged locality (0/1)	132	0.053	n/a	0	1
New locality created through merger (0/1)	132	0.219	n/a	0	1
Firefighting expenditure per capita	132	23.709	18.26916	0	161.64
Interaction term					
Tsunami height × crimes per 1000 residents	132	0.017	0.030	0.000	0.136

villages, and cities shrank from more than 3000 to fewer than 1800. Local level mergers can take place in two ways: existing municipalities can be merged together so that larger cities subsume a smaller municipality or a new area can be created based on the unification of localities. Villages, towns, and cities which have been merged may lack strong representation in local political arenas and/or lack strong identities. Social identity research on the mergers of organizations has underscored how the newly created institution (in this case the town) may not meet the expectations of members who find themselves removed from their old environments and identities (Gleibs et al., 2013).

Further, strong identification with the newly merged (or created) municipality may take extended periods of time (Gleibset al., 2008). Some scholars have suggested that recently merged communities such as Minami-Soma had "shallower" community identities than longer-established, independent communities (cf. Samuels 2013: 40); this may result in uncoordinated disaster planning and less effective evacuation. Merged or "new" localities, therefore, may have faced higher mortality rates than more established communities. Our model includes dummy variables for merged localities and new localities created through mergers.

Finally, we have included information on the height of sea walls constructed to guard localities against tsunami to reflect the amount of public investments in tsunami protection (but may be unconnected to LDP support). The Japanese central government has long sponsored the construction of sea walls to diminish the physical strength of tsunami and therefore decrease mortality risk (as was the case in Fudai Village in Iwate prefecture, with its 15 m wall, cf. *Daily Mail* 14 May 2011). Yet, such walls may weaken people's incentive to evacuate after the earthquake, creating what is known as a *moral hazard problem* in evacuation after release of a tsunami warning. Hence, we would predict that the sea wall height may have ambiguous effects on tsunami mortality.

Table 2
Exogeneity tests of explanatory variables.

	Tsunami height
Area of the municipality (square km)	0.00275
	(0.00343)
Length of paved roads	−0.00525
	(0.00889)
Population density (people/sq km)	0.000680
	(0.000577)
Crimes per 1000 residents	−5.523
	(185.194)
25 to 30% LDP support in 2009 LH election	1.540
	(1.142)
30 to 35% LDP support in 2009 LH election	1.215
	(0.610)
Above 35% LDP support in 2009 LH election	8.022
	(4.503)
Firefighting expenditure per capita	−0.00486
	(0.00833)
_cons	1.201
	(1.469)
F-statistics for a null hypothesis of jointly zero coefficients [*p*-value]	1.85 [0.351]
N	127
R-sq	0.154

Note: Robust standard errors clustered at prefectural level in parentheses.

3. Data

This new, original dataset includes all coastal municipalities, municipalities, and cities on the Pacific Coast side of the Tohoku region of Japan; this includes Iwate, Miyagi, and Fukushima prefectures. Municipalities in these three prefectures sought assistance under the national Disaster Relief Law (*Saigai kyūjo hō*). The dataset includes coastal and noncoastal localities alike because of the extent of the tsunami's inland inundation. The 133 communities in the dataset include the entire universe of localities which could have been affected by the 11 March 2011 tsunami, and there is no need to reweight the individual observations to reflect the larger distribution of cities or wrestle with truncated samples. Table 1 below describes the data used in this analysis.

Note the variation in almost all of the factors captured here — tsunami height, for example, varied from 0 to nearly 20 m (65 feet), while demographic factors such as the proportion of those over the age of 65 was distributed between 12 and 55 percent. We used a variety of sources for the data in the analysis; Table A1 in the appendix provides a comprehensive list of these sources and the dataset itself will be available on the authors' website.

4. Analysis

We begin with exogeneity tests to investigate the connection between our independent variables and tsunami height. It may be that villages with higher risk of tsunami are fundamentally different than those with lower risk because of location, demographics, or political connections. To address this concern, we examine if the strength of the tsunami itself was correlated with local demographic, social, and political conditions by regressing the tsunami height on observed community characteristics such as paved roads, population density, area size, crimes per 1000 residents, LDP party support, and firefighting expenditure.

Table 2 above shows the estimation results of regression analysis for the tsunami height variable which indicate none of the independent variables was statistically significant. The joint test results also confirm the lack of a systematic association between the tsunami height and the observed community characteristics. That is, communities which experienced no inundation at all or faced very short waves are measurably similar to those that were devastated by it. We also carried out another exogeneity test in which we divided municipalities into those in the top-quartile and lowest-quartile of tsunami height to see if there were statistically significant differences between them; there were none. With confidence that the height of the tsunami does not pose an endogeneity problem to our regression analyses, we move forward with our models.

We structured five regression models on the data to disentangle the factors which may have influenced mortality due to the tsunami. For the broader analyses and tables we employ not only the Ordinary Least Squares (OLS) method but also four nonlinear regression methods (negative binomial regression, logistic regression, zero inflated beta distribution regression, and the Tobit model). Further, Table 4 displays regression models using interaction terms to further capture non-linearity between outcome and explanatory variables. The figures displaying relationships between variables of interest use linear models. Multicollinearity and other tests of the model indicated low levels of interaction between independent variables; the VIF for the full model was less than 3.1, which is more than acceptable according to many analysts (cf. Rabe-Hesketh and Everitt, 2007: 69). Scholars lack consensus on the best ways to handle dependent variables which are proportions as we use in our model (specifically, the proportion of the local population living in inundated areas killed by the tsunami).

As such, we begin with the classic regression model, namely ordinary least squares (OLS). Because the quantity of interest is the percentage of local residents killed by the disaster (and therefore bounded at 0 and 1) and has a skewed distribution (see Fig. 1 above), standard OLS regression analysis brings with it a number

Table 3
Regression analysis results.

Model	OLS regression (robust standard errors)	Negative binomial regression (robust SEs)	Logistic regression (robust standard errors)	Zero inflated beta distribution	Tobit (lower limit at zero, robust SEs)
Tsunami height (meters)	0.00403***	0.269***	0.280***	0.121**	0.00783***
	(3.22)	(4.49)	(4.39)	(2.46)	(4.49)
Area of the municipality (square km)	−0.00000924	0.000622	0.000664	0.000712	0.0000158
	(−0.92)	(0.37)	(0.39)	(0.54)	(0.58)
Sea wall height (meters)	−0.00107	0.0856	0.0831	−0.0710	0.00267
	(−0.63)	(1.13)	(1.07)	(−1.22)	(1.56)
Coast line length (km)	0.000598**	0.0509***	0.0522***	0.0233*	0.00150***
	(2.09)	(3.34)	(3.35)	(1.95)	(3.87)
Length of paved roads	−0.00000286	−0.00578	−0.00599	−0.00499	−0.000149**
	(−0.10)	(−1.40)	(−1.43)	(−1.58)	(−2.17)
Population density (people/sq km)	−0.00000323	−0.000111	−0.000122	−0.000457**	0.000000686
	(−1.35)	(−0.49)	(−0.52)	(−2.02)	(0.19)
Pre-tsunami mortality rate	0.918*	−13.33	−11.92	107.0	0.574
	(1.73)	(−0.15)	(−0.13)	(1.52)	(0.27)
Percentage of population in fishing industry	−0.591	−35.26	−36.74	−0.682	−0.405
	(−0.91)	(−1.01)	(−1.02)	(−0.02)	(−0.43)
Percentage single-person households	−0.00340	−5.626*	−5.838*	−1.551	−0.120
	(−0.08)	(−1.70)	(−1.67)	(−0.57)	(−1.11)
Crimes per 1000 residents	1.395**	264.6***	270.7***	204.1***	6.883***
	(2.14)	(4.06)	(4.03)	(2.70)	(3.62)
25 to 30% LDP support in 2009 LH election	−0.0128**	−0.278	−0.326	−0.905**	−0.0275**
	(−2.45)	(−0.69)	(−0.79)	(−2.31)	(−2.56)
30 to 35% LDP support in 2009 LH election	−0.00980	0.194	0.160	−0.882**	−0.0162
	(−1.62)	(0.34)	(0.27)	(−2.04)	(−1.13)
Above 35% LDP support in 2009 LH election	−0.0245**	−0.609	−0.689	−1.155**	−0.0617***
	(−2.53)	(−0.46)	(−0.51)	(−2.37)	(−3.19)
Merged locality (0/1)	−0.00883	−0.350	−0.373	0.135	−0.0292*
	(−1.48)	(−0.74)	(−0.76)	(0.24)	(−1.91)
New locality created through merger (0/1)	−0.00390	−0.861**	−0.883*	−0.441	−0.0354***
	(−0.87)	(−1.97)	(−1.96)	(−0.95)	(−2.65)
Firefighting expenditure per capita	−0.000165	−0.0613	−0.0631	−0.0258	−0.000855**
	(−1.52)	(−1.15)	(−1.14)	(−1.59)	(−2.22)
Constant	−0.00114	−5.755***	−5.718***	−4.852***	−0.0427
	(−0.11)	(−3.13)	(−3.02)	(−3.84)	(−1.14)
Auxillary coefficients					
Log α	−29.42				
Tsunami height (Zero-inflated)				−1.254***	
Constant				3.674***	
Log φ				4.391***	
σ					0.0235***
N	127	127	127	127	127

Note: Robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4
Regression analysis results with interaction term.

Model	OLS regression (robust standard errors)	Negative binomial regression (robust SEs)	Logistic regression (robust standard errors)	Zero inflated beta distribution	Tobit (lower limit at zero, robust SEs)
Tsunami height (meters)	0.00221	0.274***	0.281***	0.192	0.00598***
	(1.29)	(2.83)	(2.84)	(1.56)	(2.65)
Area of the municipality (square km)	−0.00000534	0.000624	0.000665	0.00106	0.0000192
	(−0.57)	(0.37)	(0.39)	(0.77)	(0.73)
Sea wall height (meters)	−0.000519	0.0854	0.0830	−0.0703	0.00279
	(−0.28)	(1.13)	(1.06)	(−1.25)	(1.62)
Coast line length (km)	0.000318	0.0512***	0.0523***	0.0297*	0.00131***
	(0.76)	(3.65)	(3.62)	(1.91)	(2.83)
Length of paved roads	−0.00000866	−0.00581	−0.00600	−0.00625*	−0.000148**
	(−0.32)	(−1.47)	(−1.49)	(−1.69)	(−2.29)
Population density (people/sq km)	−0.00000321	−0.000117	−0.000124	−0.000542**	0.00000225
	(−1.42)	(−0.58)	(−0.60)	(−2.06)	(0.64)
Pre-tsunami mortality rate	0.849	−14.79	−12.41	85.80	0.976
	(1.63)	(-0.16)	(-0.13)	(1.10)	(0.48)
Percentage of population in fishing industry	−0.410	−35.64	−36.86	0.427	−0.291
	(−0.62)	(−1.06)	(−1.05)	(0.01)	(−0.29)
Percentage single-person households	−0.0130	−5.627*	−5.838*	−2.043	−0.125
	(−0.28)	(−1.71)	(−1.68)	(−0.71)	(−1.09)
Crimes per 1000 residents	0.971*	269.2***	272.2***	298.0*	5.419***
	(1.90)	(3.16)	(3.16)	(1.81)	(3.34)
25 to 30% LDP support in 2009 LH election	−0.0128**	−0.269	−0.323	−0.707	−0.0292***
	(−2.57)	(−0.70)	(−0.83)	(−1.42)	(−2.90)
30 to 35% LDP support in 2009 LH election	−0.00906	0.197	0.161	−0.786*	−0.0154
	(−1.52)	(0.35)	(0.28)	(−1.73)	(−1.09)
Above 35% LDP support in 2009 LH election	−0.0207**	−0.617	−0.692	−1.303**	−0.0575***
	(−2.14)	(−0.44)	(−0.48)	(−2.35)	(−2.84)
Merged locality (0/1)	−0.00657	−0.360	−0.377	−0.0422	−0.0261
	(−1.05)	(−0.68)	(−0.69)	(−0.07)	(−1.63)
New locality created through merger (0/1)	−0.00413	−0.864**	−0.884**	−0.595	−0.0352***
	(−0.94)	(−1.98)	(−1.96)	(−1.12)	(−2.65)
Firefighting expenditure per capita	−0.000160	−0.0611	−0.0631	−0.0242	−0.000835**
	(−1.34)	(−1.13)	(−1.12)	(−1.49)	(−2.25)
Tsunami height × crimes per 1000 residents	0.326	−0.634	−0.214	−8.880	0.274
	(1.56)	(−0.06)	(-0.02)	(-0.64)	(0.97)
Constant	0.00298	−5.781***	−5.727***	−5.449***	−0.0345
	(0.29)	(−2.99)	(−2.89)	(−3.48)	(−0.98)
Auxillary coefficients					
Log α		−29.42			
Tsunami height (Zero-inflated)				−1.254***	
Constant				3.674***	
Log φ				4.277***	
σ					0.0234***
N	127	127	127	127	127

Note: Robust standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

of untenable assumptions. To ensure that the results uncovered here were not artifacts of the model choice, we employ four additional models beyond OLS: a logistic regression, a negative binominal regression, zero-inflated binomial distribution model and a Tobit model with truncation at zero. Researchers have suggested that these more specialized models may better handle the characteristics of our dependent variable, namely its large number of zero cases (that is, municipalities with no casualties) and its bounds at 0 and 1 (Kieschnick and McCullough, 2003). We employ all five to demonstrate that variable affects are robust against model choice and not solely a product of the type of analysis. Table 3 below displays the estimated regression coefficients and the heteroscedasticity-robust standard errors for these five models.

Variables that proved statistically significant across almost all of our models included the height of the tsunami and mid-range electoral support for the LDP. Another variable proved very robust across model types: proportional crime rate which, as mentioned above, we interpret as a proxy for bonding social capital (Putnam 2000; Ramseyer, 2014). Across all of the five models a lack of shared norms and resulting anti-social behavior before the disaster were positively correlated with greater mortality.

We undertake one more test to see if the significance of the factors of social cohesion and wave height came about as artifacts of our regression models. We include an interaction term created by multiplying tsunami wave height by pre-tsunami levels of crime. A negative correlation between their interaction term and mortality from the tsunami would indicate that, given a level of physical strength of the tsunami, higher levels of bonding social capital (or lower levels of crime rate) can mitigate mortality. Table 4 below displays the estimated regression coefficients and the standard errors for these five models which include this interaction term.

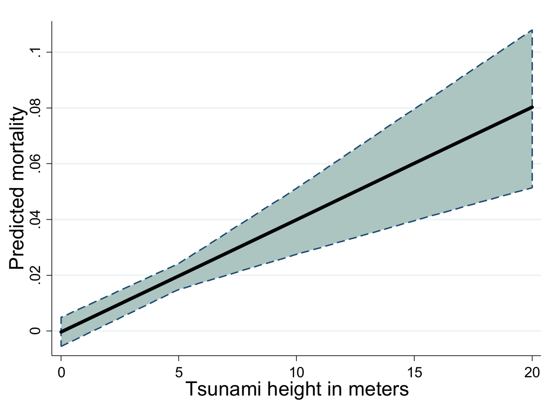
As can be seen in Table 4, the estimated coefficient on the interaction term is mixed across model types and statistically insignificant across them. We find that the relationship between social capital and tsunami height is likely additive, and not multiplicative.

Even with the relatively straightforward OLS models interpreting the actual meaning between of these estimated coefficients can be challenging. To facilitate intuitive readings of these quantities of interest, we follow King et al. (2000) in showing marginal effects plots of major variables with simulated 95 percent confidence intervals based on the OLS results of OLS reported in Table 3. We employ a statistical program which uses Monte Carlo simulations to produce confidence intervals around estimates of our variables of interest. In our simulations we set all of the other independent variables at their means and allow the independent variable of interest to vary. Through taking random draws from our distribution and then expressing the degree of uncertainty around our predictions, we can move beyond standard tables of coefficients towards more intuitively figures. This approach does not overcome data or modeling challenges; rather, it facilities interpretation of the relationship between our variables of interest.

We begin by investigating the relationship between the height of the tsunami and the mortality rate in local affected communities. Fig. 3 below illuminates the relationship between tsunami height and mortality holding all other factors in the regression model at their means. The figure shows how communities which had very short tsunami waves – fewer than two meters (six feet), for example –are predicted to have low levels of casualties (less than two percent of the population). The confidence intervals around our predicted values are narrower where the distribution of data is greater, and wider where we have less information. As the tsunami height increases casualty rates rise, to the degree that, *ceteris paribus*, a community experiencing a tsunami some 50 feet tall (15.2 m) would have a mortality rate close to five percent.

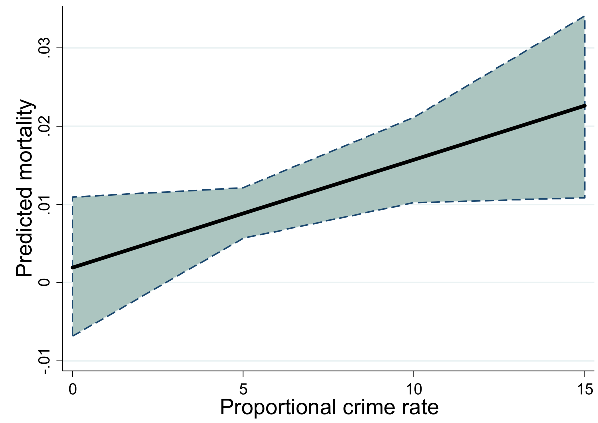
We now move to illustrate the connection between pre-tsunami crime rates and tsunami mortality outcomes. Fig. 4 below shows, holding all other factors in the model constant, the relationship between the numbers of crimes per 1000 people and the rate of mortality afterwards. As in the simulation above in Figs. 3 and 4 has wider confidence intervals around the predicted values where we are less certain of the outcomes because of a scarcity of data. Most point estimates of the crime variable shown in Tables 3 and 4 are positive and statistically significant. Despite the relative lack of data, there is a clear pattern: holding all other factors constant, communities which had higher crime rates before the tsunami will experience greater levels of mortality during it. A municipality which had 15 crimes committed per 1000 people would be expected to have a death rate some 30 times higher than one where there were only one to two crimes per 1000 people.

Finally, we move to demonstrate how different levels of support for the incumbent LDP affected levels of mortality. Fig. 5 uses the sample of localities to show how, in the raw data, higher levels of support (that is, communities where LDP support was greater than 35%) had lower death rates than those with weak or levels. However, death rates with average levels of support – between 25 and 30 percent – were almost as low as those with strong support.



Note: The shaded space represents the 95-percent confidence interval around the predicted mortality (the solid line) based on the height of the tsunami. N = 133, simulations = 1000. Tsunami height was allowed to vary while all other factors (municipality area, pre-tsunami mortality rate, population density, crime rate, sea wall height, etc.) were set to their mean values.

Fig. 3. Tsunami height and mortality rate.



Note: The shaded space represents the 95-percent confidence interval around the predicted mortality rate (the solid line) based on the crime rate before the disaster. N = 133, simulations = 1000. The pre-tsunami crime rate was allowed to vary while all other factors (municipality area, height of the tsunami, pre-tsunami mortality, population density, sea wall height, etc.) were set to their mean values.

Fig. 4. Relationship between pre-tsunami crime rate and post-tsunami mortality.

Because of the spread of the data and the difficulty of seeing this pattern in our sample, we performed 1000 simulations on the outcome to show this outcome more clearly (King et al., 2000). Holding all other factors constant, mortality rates in communities weakly supporting the LDP are predicted to hover around 2 percent (with a 95 percent confidence interval from 1 to 3 percent) while average-level supporting communities had 0.7 percent with a range from 0.3 to 1 percent. Above-average communities had mortality rates around 1 percent (with a range from 0.5 to 2 percent) and strong-supporting communities had mortality rates of 0.04 percent (with a range from 0.01 to 0.07 percent). Strong LDP support translated into statistically significantly lower levels of mortality, as did average levels of support. Tohoku communities supporting the LDP weakly – perhaps because of consequent lower levels of funding for infrastructure and investment in mitigation policies – fared worst of all.

5. Concluding remarks

Using the March 2011 tsunami as an exogenous shock to understand how local conditions influenced mortality, this paper found support for standard theories focused on the strength of the tsunami itself. This outcome was to be expected. However, beyond this prevailing factor, we found compelling evidence that the strength of social ties within and beyond communities – both bonding and linking social capital – also influencedsurvival. As a new wave of research has demonstrated, social capital and social

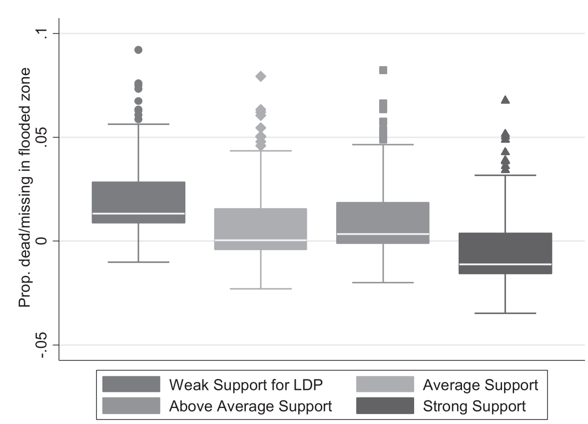


Fig. 5. Relationship between LDP support and mortality.

ties play a critical role in disaster response and recovery (Elliott et al., 2010; Hawkins and Maurer, 2010; Chamlee-Wright, 2010; Kage, 2011; Aldrich, 2012). This paper moves the field forward by providing strong support for the argument that social capital also matters during the disaster itself.

Communities which had been plagued by low trust and high crime before the disaster experienced higher rates of mortality because of an inability to self-organize and provide mutual help during a critical period. Research has shown how very similar communities with different levels of mobilization potential responded very differently to the same disaster; this happened to the side-by-side neighborhoods of Mano and Mikura in Kobe, Japan (Yasui, 2007). Following the 1995 earthquake, as fires broke out across the city, the community of Mano self-organized fire brigades to fight the conflagration, while Mikura did not (Aldrich, 2011a). In the case of the 3.11 tsunami, interviews with survivors about their behavior and the behavior of family members who did not survive illuminated that many did not evacuate upon hearing the initial tsunami warnings (Ando et al., 2013). Those who evacuated described being heavily influenced by neighbors and friends who urged them to do so or came directly to their homes to ensure their safety (Interviews with survivors 2013). Communities with lower evacuation rates were clearly at greater risk of mortality.

We would argue that deeper trust and more social cohesion made collective evacuation behavior more likely across the Tohoku area. Our models using an interaction term showed that communities facing high wave heights along with weakened social infrastructure faced double jeopardy and, as a result, higher levels of casualties. Further, strong support for the LDP resulted in measurably lower mortality rates holding all other factors constant. These extra-local ties to authorities and decision makers in Tokyo before the disaster may have provided municipalities with additional preparation policies, greater spending on disaster training, and wider safety nets during the event itself. Beyond fire fighting expenditures and other disaster-mitigation policies, strong LDP support may have resulted in higher levels of resources which helped save lives during the disaster.

These results have important policy implications for residents, NGOs, and decision makers in Japan and abroad. First, a tremendous amount of the budget (nearly $200 billion US dollars), set aside for disaster mitigation pre-3.11 and for recovery post-disaster has primarily gone into physical infrastructure, especially the construction of sea walls. A recent visit to Watari-cho, for example, found a “defense in depth” approach underway with a 7 m sea wall, 10 m wide forest, and 5 m elevated highway serving as barriers against future tsunami (author visit 8 March 2014). Yet our analysis found no support for the argument that the pre-existing seawalls provided any protection against mortality. This may have been because the average height of the sea wall was well below the average height of the tsunami. For example, in Kamaishi, the 1.2 mile long seawall cost $1.5 billion, but was nonetheless overrun by the tsunami (Onishi, 2011); this expensive infrastructure had no measurable effect on casualties.

The new investments may raise the seawalls to effective heights, but it also may be that the existence of a seawall creates a moral hazard as local community members may believe themselves safe because of its existence. If seawalls encourage residents to remain in place after an earthquake, they set up a dangerous precedent. As a side note, many fishing- and tourism-dependent communities oppose the creation of extended sea walls, fearing that these barriers may reduce the effectiveness of fishing efforts and cut down on the number of tourists interested in coming to the community. Given that ongoing recovery efforts in the Tohoku region show a great deal of money flowing into physical infrastructure projects set up through top-down planning, such spending should be rethought or at least publicly discussed with residents.

Next, research has shown that social capital – like financial and human capital – can be created through policy interventions. Japan's reconstruction budget should be allocated toward community-friendly physical and social infrastructure to reconstruct and strengthen ties among people (to facilitate accumulation of bonding, bridging, and linking social capitals). For example, the *machizukuri* (town strengthening) plan of each municipalities, location and access to public services such as government offices, hospitals, elderly and infant/child care centers, and schools should be carefully decided by community-participatory decisions. In fact, randomized field experiments in South Africa and Nicaragua have demonstrated the possibility of increasing generalized and specific trust through various policies including focus-group meetings (Pronyk et al., 2008; Brune and Bossert, 2009). Several Tohoku communities, including Onagawa, are experimenting with community currency and time banking programs which have been shown to have strong positive influences on local bonding and bridging social capital levels (Aldrich, 2012). Additionally, a number of NGOs, including the Ibasho project in Ofunato city, are working to create shared spaces where residents of all ages can regularly interact and create lasting ties (iBasho n.d.) while others are employing cooperative farming programs which have seemingly improved both social connections and physical health of participants.

Finally, many political critics have long argued that Japan's Liberal Democratic Party attracts rural voters through pork barrel spending, directed subsidies and often useless *hakamono* (empty box) or road-to-nowhere projects (cf. Bardhan, 1997). Corruption scandals have regularly graced the front pages of newspapers and eroded trust in governing institutions (Pharr and Putnam, 2000). Even major changes to Japan's electoral institutions in the early 1990s – such as replacing the single, non-transferable vote (SNTV) system with single-member districts (SMD) and proportional representation (PR) - have caused few large-scale changes in electoral politics (Scheiner and Tronconi, 2011). Negotiations over participation in international institutions – such as the Trans-Pacific Partnership – intended to liberalize trade and reduce the protection of domestic interest groups have instead resulted in additional redistribution to rural constituencies (*Nikkei Report*, 26 March 2013). Our findings underscore the continued role of clientelistic politics in rural Tohoku communities and suggest the need to ensure better and more equitable policies in such areas in the future.

As we move into the 21st century, we enter an era when the number of disasters and their physical costs are only increasing; anthropogenic global warming and urbanization amplify these trends of extreme weather events and greater vulnerability. In Japan and around the world governments must recognize that, given the ubiquity and likelihood of disaster, resilience and recovery will come from a combination of government-, market-, and community-led efforts (Aldrich et al., 2014). This article has shown that, while factors such as wave height and local demographics may be immutable, other critical ones, especially social cohesion, should be the target for policy programs at the local, regional, and national levels.

Ethics approval

This paper requires no ethics approval as no data was collected from human subjects. Instead, all of the data used in the paper come at the aggregate level from publicly available sources.

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Appendix

Table A1
Data sources

Variable	Source
Tsunami height (meters)	The 2011 Tohoku Earthquake Tsunami Joint Survey (TTJS) Group (http://www.coastal.jp/ttjt/index.php)
Area of the municipality (square km)	Ministry of Internal Affairs and Communications (MIAC), Statistics Bureau (http://www.stat.go.jp/data)
Sea wall height (meters)	Ministry of Land, Infrastructure, Transport and Tourism (http://www.thr.mlit.go.jp/)
Percentage of population in fishing industry	Ministry of Internal Affairs and Communications (MIAC), Statistics Bureau (http://www.stat.go.jp/info/shinsai/)
Percentage of single-person households	Ministry of Internal Affairs and Communications (MIAC), Statistics Bureau (http://www.stat.go.jp/data)
Percentage of population over 65	Ministry of Internal Affairs and Communications (MIAC), Statistics Bureau (http://www.stat.go.jp/info/shinsai/)
Population density (people/sq km)	Author's calculation (people per square kilometers, data from MIAC)
Crimes per 1000 residents	Ministry of Internal Affairs and Communications (MIAC), Statistics Bureau (http://www.stat.go.jp/data)
LDP party support in 2009 LH election (proportion)	Calculations from database of elections undertaken by Steven Reed
Merged locality (0/1)	Japan Post Service Co. (http://www.post.japanpost.jp/zipcode/merge/prefecture.html)
New locality created through merger (0/1)	Japan Post Service Co. (http://www.post.japanpost.jp/zipcode/merge/prefecture.html)
Firefighting expenditure per capita	Iwate, Miyagi, and Fukushima Prefectures

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