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Article

Substitute or complement? How social capital, age and socioeconomic status interacted to impact mortality in Japan's 3/11 tsunami

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ABSTRACT

Background: Research underscoring the critical nature of social capital and collective action during crises often overlooks the ways that social ties interact with vulnerability factors such as age and socioeconomic status.
Methods: We use three different data structures and five types of regression models to study mortality rates across 542 inundated neighborhoods from nearly 40 cities, towns, and villages in Japan's Tohoku region which was flooded by the 11 March 2011 tsunami.
Results: Controlling for factors thought important in past studies - including geographic administrative, and demographic conditions - we find that social capital interacts with age and socioeconomic status to strongly correlate with mortality at the neighborhood level. For the elderly and those with lower socioeconomic status, *ceteris paribus*, deeper reservoirs of social capital are linked with lower levels of mortality.
Conclusion: While most societies invest heavily in physical infrastructure to mitigate future shocks, this paper reinforces the growing call for spending on social infrastructure to develop communities which can cooperate and collaborate during crises. For the elderly and poor, social ties can serve as a literal lifeline during times of need.

1. Introduction

A growing body of literature has found evidence that social ties - that is, social capital, cohesion, and collective action - are critical elements in crises (Aldrich, 2019; Beggs, Haines, & Hurlbert, 1996; Bucklan & Rahman, 1999; Olson, 1965). At the same time, scholars have made clear that not all members of society have equal access to or benefits from important resources such as social ties (Valtorta & Hanratty, 2016; Meyer, 2017). Precisely how social ties and vulnerability factors - such as age and socioeconomic status-interact during an event such as a region-wide tsunami remains unclear.

This paper uses a new dataset on more than 542 neighborhoods across nearly 40 cities, towns, and villages in Tohoku to study the factors at the community level which influenced mortality during the tsunami. Using Japan's 3/11 catastrophe as a natural experiment, it investigates the degree to which social ties altered mortality rates and then whether socioeconomic status and age interacted with social ties during the crisis.

Our paper adds to the existing literature in several ways. First, it moves beyond analyses at larger administrative units of social capital and mortality during the 3/11 disasters (cf. Aldrich & Sawada, 2015; Nateghi et al., 2016) down to a micro-level dataset at the neighborhood level. As we explain in more detail below, our community level data (*machi ōaza*) can provide a more detailed picture of interactions between people, their neighbors, and local social infrastructure during crisis than previous research done at the city or village level (Patterson, Weil, & Patel, 2009).

Next, while some studies of disasters have focused primarily on the role of social capital, we follow the advice of past scholars to interact data on social capital with factors of vulnerability, such as age and socioeconomic status (Durant, 2011; Reininger et al., 2013). This builds on a growing recognition of the importance of taking income, education, and age-related factors into account in disaster research (Fothergill & Peek, 2004; Frankenberg, Sikoki, Sumantri, Suriastini, and Thomas 2013).

We also try to shed light on an interesting puzzle: where some have argued that low socioeconomic status (hereafter SES) correlates with low levels of social capital, leading to poor health outcomes, others have argued that social capital can substitute for reduced SES to mitigate such negative consequences. In this sense we are studying to see if SES and social capital serve as substitutes - uncorrelated, so that poor communities can have better health outcomes in crisis because of

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deeper reservoirs of social capital - or complements, where they group together and are highly correlated. In such a case, with low levels of socioeconomic status and shallow reservoirs of social ties, already vulnerable communities would be at greater risk.

Finally, despite a growing body of literature emphasizing the positive impact of deeper social ties on individual and community health across disaster types (Kawachi, Subramanian, & Kim, 2008; Kemp, Arias and Garcia 2018), a handful of studies of mortality following the 3/11 disasters have suggested social capital's impact may not always be positive (Aida et al., 2017). Stepping beyond this simple binary disagreement, our analysis suggests that communal levels of social cohesion have nuanced and targeted effects rather than broad-based ones. Hence higher levels of social ties may not provide similar benefits to all in a community but remain a critical resource for the most vulnerable.

This paper lays out the background of the study, illuminates the factors which could influence mortality rates during crisis, tests their impact on mortality through a variety of quantitative regression models, and then concludes with broader lessons for disaster managers and decision makers.

1.1. Study background: The 3.11 Triple disasters

At 2:46 pm on 11 March 2011 a massive, 9.0 magnitude earthquake struck off Japan's northeast region. That earthquake set off a series of tsunami and a nuclear meltdown which resulted in the direct deaths of more than 18,400 people across the Tohoku region (National Police Agency, 2018). The massive waves, more than 20 m (60 feet) in some areas, damaged or destroyed some one million residences and businesses along the coast. Mortality levels varied tremendously across Tohoku. In some towns, villages, and cities, for example, more than 10 percent of the population died during the tsunami. In others, however, no one perished. The tsunami, and not the earthquake, was the major cause of death for most of those who passed away.

Not everyone living in coastal areas drowned or was crushed by the black waves, however. Between the earthquake and arrival of the first tsunami, some 40 min elapsed. In that period of time, younger, healthier, and more able-bodied residents who were in vulnerable coastal locations moved from their homes and businesses up to high ground (*takadai*). The elderly, those who were unaware of the impending tsunami, and the infirm often could not escape the oncoming waves on their own (Aldrich, 2019). As with past disasters, tsunami victims were often elderly (Doocy, Gorokhovich, Balk, and Robinson 2007) so that "mortality showed a tendency to increase with age" (Nakahara & Ichikawa, 2013).

Vulnerable residents without neighbors, friends, or family to act as rescuers were at higher risk of death (Muir-Wood, 2016: 198). Those living in active and engaged communities, however, saw neighbors, volunteer firefighters, friends, and family members entering their homes and hospital rooms to warn and rescue them. In some cases, prosocial behavior involved carrying the vulnerable on their backs, putting them on mopeds, or giving them a ride in a car or van to a safer location (Branigan, 2015). The degree to which communities experienced mortality during the tsunami, then, may be a measure of their ability to engage in mutual aid and cooperation at a moment involving high risk (Takezawa, 2016).

2. Theoretical framework

This study builds on past research which has highlighted the importance of a number of factors, including social capital, age, and socioeconomic status (SES) alongside control variables for the geographic and administrative environment, which may influence mortality during disasters.

Much research has illuminated the role of **social capital** during crises (Bucklan & Rahman, 1999; Dynes, 2005; Aldrich, 2012). To begin, we follow a standard approach to defining social capital as "networks, norms, and trust … that facilitate action and cooperation for mutual benefit" (Putnam, 1993, p. 35). Social capital and social ties (we will use these phrases interchangeably) operate at the individual and community levels, and these ties come from interactions with neighbors, workplace colleagues, and decision makers and also from connections to institutions whether faith based, cultural or sport in nature (Szreter & Woolcock, 2004).

At the micro level of society, social ties have proven important during crises for a number of reasons (Olson, 1965). Weak and strong connections provide information, resources, and moral support at critical junctures (Granovetter, 1973; Beggs et al., 1996). Stronger social cohesion facilitates collective action and group mobilization, allowing residents to cooperate even under duress (Olson, 1965). Research on disasters has indicated that higher levels of community social capital created more positive recovery processes and higher reports of satisfaction (Nakagawa & Shaw, 2004). As we will discuss below, we use several indicators of social capital tied together in an index to take into account participation in voluntary groups along with social infrastructure levels.

Alongside social capital, we include proxies for **age** recognizing past studies that have shown the elderly (and the very young) tend to have higher levels of mortality during disasters of all kinds (Frankenberg, Laurito, & Thomas, 2014). Focusing on age is important as Japan's greying problem is more critical than in other countries, especially in the periphery (Mathieu et al., 2015). In these coastal communities in Tohoku, the mean age across residents is higher than the national average, and there are far more elderly than young people. These pre-disaster demographics magnified the impact of the triple disasters. One study of the Tohoku tsunami argued "the death rates in the age classes of those over 60 were exceptionally high: it was 10–13% for those in their 60s and 70s and 18% for those older than 80" (Koyama et al., 2012).

Age and mortality correlate for a number of reasons. The elderly may already have frail physical conditions because of past diseases or ongoing struggles with cardiovascular or neurodegenerative challenges. A physical hazard like the tsunami would exacerbate such conditions. Because of decreased mobility, the elderly may be unable to leave vulnerable areas before the arrival of a life-threatening hazard like the massive waves which came ashore on 11 March 2011.

Beyond studying age in isolation, we are interested in the *interactions between age and social ties*. While in the past, extended families in Japan lived together in a single household, over time intergenerational living has declined. At the same time, greater social and geographical mobility and fewer economic opportunities in peripheral communities have led to a rise in one-person households, making the elderly more socially isolated (Valtorta & Hanratty, 2016). This kind of isolation leads to higher mortality during non-crisis times compared to that of younger people (Seeman, Kaplan, Knudse, Cohen, & Guralnik, 1986); *a fortiori* elderly residents who are isolated during disasters may face higher risks. Elderly people are more likely to report fewer social ties than middle age and younger people and therefore be unable to take advantage of the benefits of group mobilization and collective action, a factor we will discuss in more detail shortly (Meyer, 2017). With more elderly living alone, they need the assistance and information provided by ties and neighbors.

We also seek to include measurements for **socioeconomic status**. We do so for a number of reasons. It is likely that the quality of infrastructure - such as the resistance of homes and businesses to shocks like earthquake and tsunami - would be higher in communities with higher income and better education levels. Similarly, communities with more education and higher paying jobs may be more likely to have early warning systems, engage in disaster training, and receive information on potential threats like tsunami (Fothergill & Peek, 2004). Finally, according to the Kuznets Hypothesis, as income rises, inequality increases, and past studies have shown increasing base mortality rates correlating with inequality (Kawachi, Kennedy, Lochner, Prothrow-

Smith, & Deborah, 1997; Kuznets, 1955; Ram, 1989).

Recognizing that SES may affect mortality differently depending on the presence or absence of trust and cooperation, we seek to understand the *interaction between social capital and socioeconomic status* because of two conflicting findings from past studies. Some have argued that socioeconomic status and levels of social capital are correlated so that poorer communities have less engagement, trust, and cohesion (Han, Chu, Song, & Li, 2014; Subramanian, Lochner, & Kawachi, 2003). This may be because poorer communities with less education have less free time to form and maintain social networks or because of negative interactions with each other and authorities. Lower SES communities may have more bonding than bridging social capital, enabling them to only “get by” but not to “get ahead.”

On the other hand, some scholars have seen social ties substituting for weak SES levels. Economic stresses, such as being an unskilled worker, lacking effective health insurance, and requiring sick leave impact the health and wellbeing even in relatively egalitarian societies. Yet social capital may mitigate some of those negative impacts (Lindstrom, Rosvall, & Lindstrom, 2017). Communities with lower levels of socioeconomic status need to draw more heavily on their social ties and safety nets during crisis, as social capital can minimize obstacles created by low levels of SES (Elgar, Trites, & Boyce, 2010). Our paper can help shed light on this question if social capital has more effect among the lower SES communities or higher SES communities.

Beyond the social capital and demographic factors which may influence mortality, we also seek to control for a number of **environmental factors** which may have influenced morbidity. Past studies argued that geographic features, such as differences in topography among the *ria* coastal area in Tohoku, can account for differences in mortality due to inundation variation (Ishiguro & Yano, 2015; Suppasri et al., 2016). Other scholars have argued that physical mitigation structures, such as seawalls and berms, impacted mortality rates during the 3/11 tsunami (Nateghi et al., 2016), although scholars have found little evidence for these claims (Aldrich & Sawada, 2015). We now look to explain the data and methods used in our analysis.

3. Data

To create a new dataset of all communities affected by the 11 March 2011 tsunami we used a variety of sources including Japan's Ministry of Land, Infrastructure, and Transport (MLIT), Japan's Statistics Bureau, Japan's national census, and corrected mortality data from previous scholarship (Tani, 2012). Our dataset of 542 neighborhoods draws on nearly 40 coastal cities, towns, and villages in the most affected areas of the Tohoku region in Iwate, Miyagi, and Fukushima Prefectures. Fig. 1 below illustrates the geographic region of Japan under study here.

Rather than serving as a partial sample, our dataset encompasses all registered, inundated neighborhoods in the Tohoku region.

A full list of the sources for our variables can be found in Appendix Table 1 and a list of the cities, towns, and villages from which we drew our sample can be found in Appendix Table 2. This study uses the neighborhood (*machi ōaza* in Japanese) as its level of analysis, with each geographic unit holding an average population of approximately 1468 people and a mean area of 7.25 km^2 in the inundated communities under study here (Tani, 2012). In terms of population size, this is analogous to the block group of the United States (with an average size of around 1500 people per block, although of course, many blocks in North America have no population). We drop all neighborhoods with less than 1 m inundation as the mortality risk from such low level flooding was quite low (Koyama et al., 2012).

We use this level of data on Japanese communities for a variety of reasons. Using micro-level neighborhood data allows us to better understand small-scale social interactions and societal frameworks than both individual surveys and broader scale, meso or macro level data (Kobayashi, Suzuki, Noguchi, Kawachi, and Tako 2015). Community-level data provides an integrated vision of local society that is more challenging to capture with the individual- or city-level information (Aida et al., 2011). Past research on mortality during 3/11 has relied on broader level administrative units such as cities, towns, and villages (*shi, cho and son* in Japanese) that encompass dozens, if not more, smaller neighborhoods and communities (Aldrich & Sawada, 2015). This study, like other recent studies of the triple disasters, takes one step forward in the field by using more localized information (Hasegawa, Suppasri, Makinoshima, & Imamura, 2017).

Because our unit of analysis sits at the neighborhood level, we can also better capture a critical independent variable, namely social capital. As social capital is often generated through regular, daily routines in a defined geographic space it can be challenging to measure using arbitrary, large-scale administrative boundaries such as zip codes or city boundaries. Citizens envision themselves as dwellers in their hyperlocal community rather than merely residents in the larger city. For Tohoku residents, smaller scale neighborhoods, like those in other parts of Japan, serve as “socially significant and geographically distinguishable divisions of the urban landscape” (Bestor, 1989, p. 1).

In order to visualize the advantages of this level of analysis, we provide an example of neighborhoods in the city of Tagajo in Miyagi Prefecture in Fig. 2 below.

3.1. Dependent variable

Our core dependent variable is the tsunami-related normed mortality at the *machi ōaza*-level in coastal communities of Iwate, Miyagi and Fukushima Prefectures. We calculated this outcome by dividing the number of deaths in each neighborhood by the resident population there. In order to compare the effect of social capital on mortality between younger and elderly people, we also employ different measures of the mortality of people whose age are under 65 and those over 65. Out of the 542 communities under study here, 128 communities, or roughly 20 percent, saw no tsunami-related deaths among those 65 and over. The others experienced mortality rates for the elderly varying between 0 and 80% (a tragedy which occurred in the Isobe neighborhood of the city of Soma).

3.2. Independent variables

Our independent variables include social capital, socioeconomic status, and a number of control variables.

3.3. Social capital

Our core variable of interest is in social capital, that is, the norms and ties among and between local residents in communities (Putnam, 1993, 2000). As no single proxy can holistically capture the levels of social capital in a neighborhood, we follow past precedent by constructing a normed social capital index using principal component analysis (Rupasingha, Goetz, & Freshwater, 2006) using three variables: cultural centers (*kōminkan*), public facilities (including gyms, libraries, and gardens), non-profit organizations (NPOs, *tokutei hieri katsudō hōjin*). These capture different facets of social ties, including participation in horizontal associations, civic engagement, and social infrastructure.

We use NPOs as past scholarship has argued that they serve to enrich the local social fabric of the community and simultaneously as a measure of civic engagement (Putnam, 2000). NPOs in Japan include groups classified by the Japanese government as nonprofit public-interest entities such as schools, religious institutions, and medical and social welfare organizations (Aldrich, 2012). Past scholars regularly use NPOs as an indicator of the depth of social ties in a community (Sakurai, 2007; Tanaka, 2007; Kanaya, 2008; Kusakabe, 2002).

Along with NPOs density, we capture the number of cultural centers in the community per 1000 people as a measure of social capital (cf. Ogino, 2014). These facilities help residents meet, engage in mutual

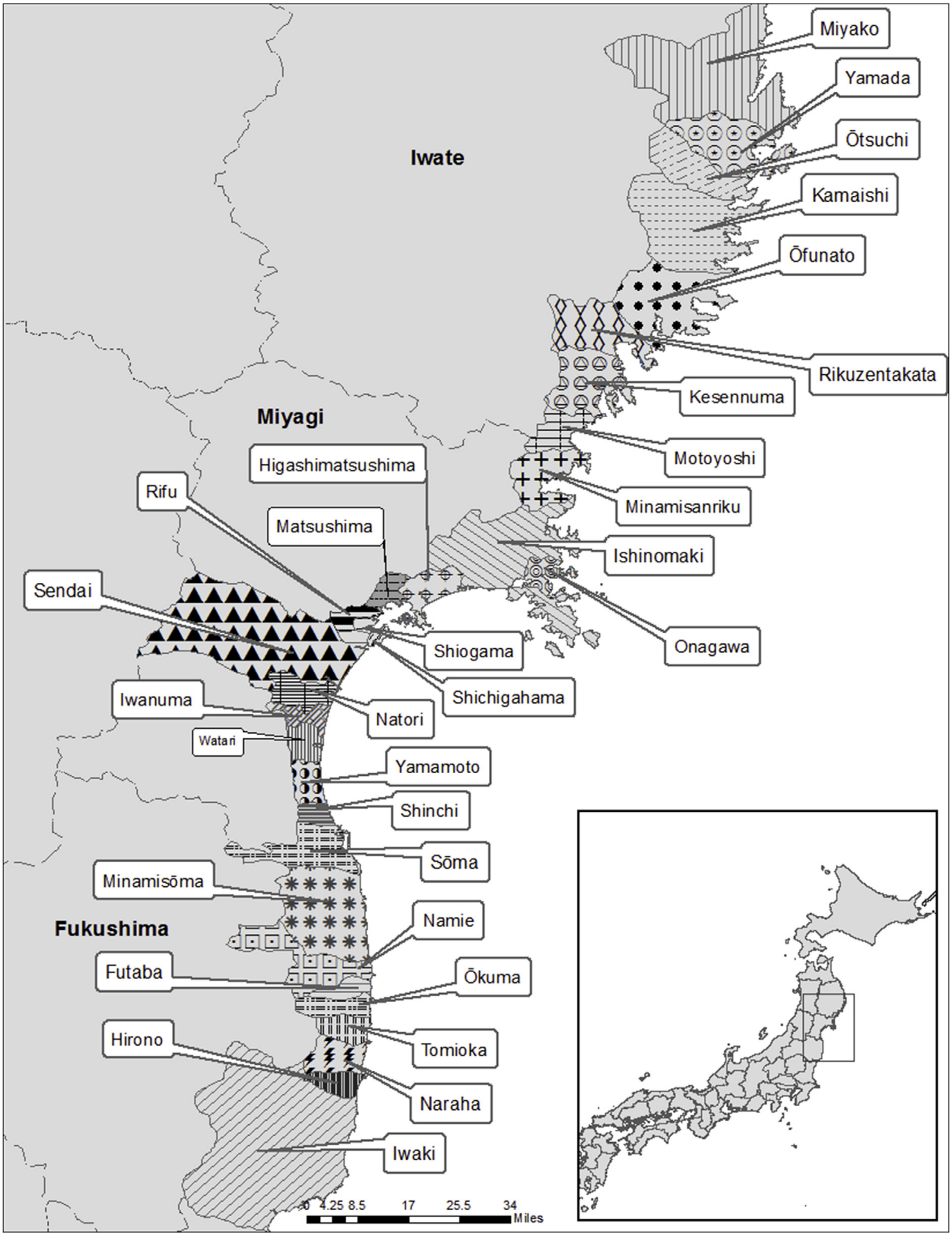

Fig. 1. Coastal areas under study.

teaching and learning (Ministry of Education, 2008) and create social capital among the communities (Glover, 2004). One study of communities in Japan indicated that *Kōminkan* helped create social capital in local areas in Japan (Ogino, 2014). Cultural centers, such as the ones created through the Ibasho program in Massaki-cho, have built broader social networks, more efficacy, and a sense of place in the community (Aldrich & Kiyota, 2017).

Finally, we also look to study the density of public facilities that create social capital in the neighborhood. Public libraries increase interactions among the citizens by providing a free learning place (Aabø, Audunson, & Vårheim, 2010; Ferguson, 2012; Svendsen, 2013), while gyms enhance the friendship and trust among the citizens through the

Fig. 2. *Machi ōaza* -level communities in the city of Tagajo.

team sports (Elmose-Østerlund, van der, & Jan-Willem, 2017; Mathieu et al., 2015; Seeman, Kaplan, Knudse, Cohen, & Guralnik, 1986). Public gardens offer a communal place for citizens' daily life helping to promote communication as a third space (Alaimo et al., 2010).

3.4. Socioeconomic status

This study employs three proxies to capture the socioeconomic status across our communities: education level, occupation, and industry. We categorize education into three levels: junior high school, high school, technical college and university degree. We include management, professional, official and general staff in our measure of employment and divide industries into primary, secondary and tertiary industries. We apply a hierarchical cluster analysis to divide communities into higher, middle and lower socioeconomic status. Lower SES communities have a higher proportion of primary school educated residents engaged in general-occupational and primary industries. Middle socioeconomic status communities have higher proportions of high school educated and secondary industry workers. Higher socioeconomic status communities have the highest proportions of college/university educated individuals and they work primarily in management, professional and office jobs.

3.5. Control variables

Geographic and physical infrastructure along with broader demographic conditions may alter mortality outcomes at the neighborhood level. Following past studies (Aldrich & Sawada, 2015; Browning, BrowningWallace, Feinberg, & Cagney, 2006), we include tsunami height, the area of the community, coastline length, seawall height, population density, the proportion of those aged 65 and over, the proportion of single-person households, and residential stability. Residential stability is calculated as the percentage of the population living in the same community as five years ago.

To improve the accuracy of our estimations, we added three other control variables to the analyses, namely designated city status, proportion of women in the population, and the distance between the sea and the nearest mountain. The designated city variable is applied to control for the influence of Sendai city communities as Sendai serves the central city of Tohoku region by mandate of the central government. Communities within it may have different mitigation infrastructure or demographics than elsewhere. We measure distance between the water and higher ground as a shortest distance between the sea and the nearest mountain to capture the geography of evacuation. The descriptive statistics of all the variables are shown in Table 1 below.

4. Analysis

4.1. Analysis strategies

In order to estimate the effect of the independent variables, and to make sure that our findings were not an artifact of model type, we conducted five types of regression including ordinary least squares (OLS), logistic regression, Poisson regression, Zero-inflated Poisson (ZIP) regression and negative binomial regression for analyses. These multiple models also helped eliminate the challenges that can come from working with a bounded dependent variable, namely normed mortality in the community, which sat between 0 (no residents died in the tsunami) and 80 (four-fifths passed away). In our statistical analyses, we avoid the ecological inference problem - that is, seeking to draw conclusions about individuals - by keeping focus on the neighborhood (Kawachi, Kennedy, Lochner, and Prothrow-Smith 1997) and not making claims about individuals.

4.2. Coefficient comparison

Our core analysis of the variables requires us to go beyond our basic models. Because we seek to understand the potential varying effect of social capital on the mortality of young and old at the community level, we set up our regressions to enable us to do so through three methods which can check the equality (difference) of the coefficients for these

Table 1
Descriptive Statistics of Variables.

Variables	N	Mean/Percentage	Standard Deviation	Min	Max
Dependent Variable					
Tsunami mortality (proportion of dead in inundated areas)	542	2.396	3.900	.000	38.410
Under 64 tsunami mortality (proportion)	542	.013	.026	.000	.290
65 and older tsunami mortality (proportion)	542	4.776	7.900	.000	80.000
Independent Variables					
Social capital (index)	542	.002	1.169	-.517	14.371
NPO number per 1000 people	542	.252	.998	.000	11.905
Kominkan number per 1000 people	542	1.444	4.009	.000	45.455
Public facility number per 1000 people	542	.415	1.428	.000	20.000
Demographic variables					
Socioeconomic (SES) status index	542				
Lower SES	127	23.430		.000	1.000
Middle SES	184	33.950		.000	1.000
Higher SES	231	43.620		.000	1.000
Population density (log)	542	6.341	1.701	2.388	10.128
Proportion 65 years and older	542	.305	.094	.041	.854
Proportion of women in the population	542	.518	.031	.364	.617
Proportion of single-person households	542	.228	.122	.000	.854
Residential stability (Proportion of people who lived in the same neighborhood 5 years ago)	542	.841	.113	.097	1.000
Geographic variables					
Tsunami height (m)	542	6.682	5.004	1.000	22.769
Area of the community (square km)	542	7.249	46.012	.003	991.877
Coast line length (km)	542	2.171	4.502	.000	41.480
Distance between sea and nearest mountain (km)	542	1.412	1.858	.000	11.100
Seawall height (m)	542	6.949	2.840	.000	15.500
Administrative variables					
Designated city dummy	542				
No = 0	521	96.130		.000	1.000
yes = 1	21	3.870		.000	1.000

cohorts. To do so, we need to carry out more specialized methods that can help us evaluate the differences between the morbidity rates of the old and young. First, we used a "stacking" method which temporarily doubles the number of observations (to 1084) to create two dependent variables: mortality for those under 64 and mortality for those over 64 (Stata, 2018). We kept all other variables the same in the two "new" datasets. This enabled us to compare the effects of social capital on mortality for those 64 and under with those over 65. Next, for the second stage of the stacking method, we combine these two datasets into one and create a binomial variable labeled *Age* to distinguish the mortality rates of the groups (under vs. over 64). Finally, we include social capital, age and the interaction term between social capital and age in the regression models. Our variable here is the significance of the difference between the coefficients of the two age categories.

While stacking is the simplest analytically it is also the most unorthodox, so we carried out a second analysis using seemingly unrelated (SU) modeling with T-tests (Haberman & Ratcliffe, 2015; Weesie, 1999). Finally, to ensure that our results were not the artifacts of stacking or the SU models, we also used structural equation (SEM) modeling and a T-test (Kwan & Chan, 2011) as a third way to understand the differences on social ties between the young and old. For more details on the stacking approach, please see Appendix 2 (Notes on Methodological Details).

4.3. Results

Before going into the multivariate analysis, we want to first demonstrate the univariate association between the dependent variable and main independent variables as seen in Table 2. This table indicates that the social capital index and SES index are negatively associated with mortality while age is positively associated with mortality. In order to clarify if these associations are significant and not mediated by other control variables, we carry out five types of regressions in Tables 3 and 4. Table 3 displays the estimated coefficients for social capital proxies and socioeconomic status while Table 4 displays the results of social capital and age.

In Table 3, we further divide the results of the five regression models into two columns. The left column displays the main effect of social capital and socioeconomic status (SES) on tsunami mortality. The right column for each model output adds an additional interaction term between social capital and socioeconomic status.

As seen in the left column of each model, the social capital index is negatively and significantly associated with the tsunami mortality. As social capital rises, mortality falls at the community level, consistent with previous studies about social ties and morbidity (Aldrich, 2019; Aldrich & Sawada, 2015). In the OLS regression model, for example, the coefficient for the social capital index is -0.25, meaning if the social capital index in the communities increases one unit, the disaster-related mortality will decrease 0.25 holding all other variables in the model constant.

Setting the middle SES communities as the reference variable, we see that only lower socioeconomic status is positively and significantly associated with mortality. That is, compared with middle SES neighborhoods, tsunami mortality is higher in the lower SES communities.

Table 2
Correlation among the Dependent Variable and Main Independent Variables.

Variable	Correlation with Mortality	Correlation w Social Capital Index	Correlation w/SES Index	Age
Mortality	1.000			
Social Capital Index	-.053	1.000		
SES Index	-.033	.061	1.000	
Age	.393	-.000	.000	1.000

Table 3
Social Capital and Socioeconomic Status Results.

	Model 1		Model 2		Model 3		Model 4		Model 5	
	OLS		Logit		Poisson		ZIP		Negative Binomial	
Social capital index	-.251 +	-.012	-.244*	-.157	-.238***	-.023	-.267***	.020	-.197**	-.019
	(.135)	(.360)	(.108)	(.259)	(.043)	(.068)	(.047)	(.071)	(.069)	(.121)
Socioeconomic status index (Ref: Middle SES)										
Lower SES	1.498***	1.483***	.822*	.823*	.451***	.338***	.415***	.275***	.472**	.392*
	(.454)	(.453)	(.390)	(.398)	(.074)	(.077)	(.077)	(.081)	(.161)	(.164)
Higher SES	-.426	-.457	-.711*	-.730*	-.155 +	-.158 +	-.130	-.149 +	-.245	-.264 +
	(.420)	(.422)	(.323)	(.326)	(.084)	(.085)	(.088)	(.089)	(.154)	(.154)
Interaction term										
Social capital index*Lower SES		-.690*		-.390		-.550***		-.690***		-.631**
		(.419)		(.356)		(.107)		(.114)		(.203)
Social capital index*Higher SES		.016		.062		-.050		-.111		-.097
		(.406)		(.294)		(.093)		(.098)		(.157)
Population density (log)	.390**	.405**	.729***	.736**	.105***	.102***	.078**	.075**	.146**	.148**
	(.135)	(.134)	(.126)	(.127)	(.024)	(.024)	(.026)	(.026)	(.050)	(.050)
Proportion 65 years and older	1.375	2.188	-.403	-.086	.356	.636	1.066*	1.576***	1.529	2.189*
	(2.205)	(2.223)	(1.691)	(1.745)	(.391)	(.395)	(.440)	(.442)	(.986)	(1.009)
Proportion of women in the population	3.521	3.169	5.853	6.005	2.450*	2.329*	.378	-.235	.860	-.318
	(5.652)	(5.661)	(4.200)	(4.31)	(1.000)	(.980)	(1.199)	(1.160)	(2.217)	(2.266)
Proportion of single-person househlds	2.018	1.992	2.266 +	2.294 +	1.420***	1.394***	1.354***	1.376***	2.042**	2.026**
	(1.756)	(1.751)	(1.308)	(1.320)	(.343)	(.339)	(.363)	(.357)	(.685)	(.683)
Residential stability	4.188*	4.218*	2.138	2.121	2.429***	2.339***	2.500***	2.410***	2.634**	2.403**
	(2.021)	(2.016)	1.426	(1.428)	(.470)	(.469)	(.506)	(.510)	(.874)	(.873)
Tsunami height (m)	.295***	.298***	.184***	.192***	.010***	.101***	.091***	.093***	.124***	.128***
	(.037)	(.037)	(.035)	(.036)	(.006)	(.006)	(.006)	(.006)	(.015)	(.015)
Area of the community (km2)	-.003	-.003	.136**	.134**	-.002	-.001	-.002	-.002	-.002	-.002
	(.003)	(.003)	(.052)	(.051)	(.001)	(.001)	(.001)	(.001)	(.002)	(.002)
Coast line length (km)	-.101**	-.098**	.070	.073	-.034***	-.032***	-.041***	-.038***	-.027 +	-.028 +
	(.038)	(.038)	(.081)	(.084)	(.008)	(.008)	(.009)	(.009)	(.015)	(.015)
Distance between sea and nearest mountain (km)	.829***	.834***	.311**	.329**	.286***	.289***	.284**	.288***	.380***	.378***
	(.121)	(.120)	(.114)	(.114)	(.018)	(.018)	(.018)	(.018)	(.052)	(.051)
Seawall height (m)	-.037	-.058	-.094*	-.105*	-.018	-.023 +	-.014	-.020	-.003	-.011
	(.057)	(.058)	(.044)	(.045)	(.012)	(.012)	(.013)	(.013)	(.024)	(.024)
Designated city dummy (Ref: No)	−4.167***	−4.097***	-.795	-.766	−1.463***	−1.425***	−1.550***	−1.507***	−2.072***	−1.993***
	(1.072)	(1.068)	(.934)	(.932)	(.187)	(.187)	(.191)	(.102)	(.471)	(.465)
Constant	−8.946**	−8.989**	−9.688***	−9.854***	−4.614***	−4.489***	−3.481***	−3.158***	−5.123***	−4.472***
	(3.310)	(3.319)	(2.498)	(2.532)	(.678)	(.676)	(.755)	(.740)	(1.308)	(1.324)
Tsunami height (m)							-.060	-.056		
							(.046)	(.043)		
Constant							−1.891***	−1.912***		
							(.391)	(.385)		
Log α									.144	.117
									(.094)	(.095)
α									1.154	1.124
									(.109)	(.107)
R2/Pseudo R2	.210	.220	.199	.204	.195	.205			.072	.078

Notes: Numbers in parentheses are standard errors. N = 542.
$+ p < .10$, $*p < .05$, $**p < .01$, $***p < .001$.

These findings fit with arguments about the lower quality of buildings and residences along with comparatively fewer warning systems in such neighborhoods. The coefficient in the OLS regression, for example, is 1.50, demonstrating that the average mortality in lower communities is 1.50 percentage higher than that in middle communities.

In the right column (except for the logistic regression model), the interaction term between the social capital index and lower levels of SES is negative and significant. When we include the interaction term, the main effect of social capital (in isolation) becomes non-significant, indicating that the effect of social capital on the mortality exists most strongly in the lower SES communities. The coefficient of the interaction term between the social capital index and lower SES levels in the OLS regression is −0.69, meaning that if social capital in the lower SES communities increases one unit, the disaster-related mortality will decrease 0.69 percentage *ceteris paribus*.

Other variables, including tsunami height, the distance between sea and mountain, residential stability and single-person household are consistently and positively associated with the disaster-related mortality while the designated city status is negatively associated with mortality.

Now, turning to Table 4, we investigate the main effect of age on tsunami mortality in the left column of each model again including the interaction term between social capital and age in the right column. We first use the under 64 category as reference, and demonstrate that the coefficient of age is positively and significantly consistent in each model except for the logit model. Compared with people under 64, the tsunami mortality of 65 and older people is higher, as expected from the literature. In the OLS regression, for instance, the coefficient is 4.76, means the average mortality among 65 and older people is 4.76 percentage points higher than that among people under 64.

We focus on results from the OLS model, where the interaction term between the social capital index and age is negative and significant. The other models are less trustworthy here, as can be seen from their higher standard errors. This is likely because of the multicollinearity between the main effect and the interaction term in these models. In addition, according to Mustillo, Lozardo, and McVeigh (2018), the interaction term is only meaningful in OLS regression models, and it is not meaningful in other non-linearity models, such as logistic regression and

Table 4
Social Capital and Age Results.

	Model 4		Model 5		Model 6		Model 7		Model 8	
	OLS		Logit		Poisson		ZIP		Negative Binomial	
Social capital index	-.241 +	.031	-.257***	-.342**	-.228***	-.307	-.203***	-.284	-.180**	-.315
	(.146)	(.201)	(.078)	(.120)	(.031)	(.605)	(.036)	(.599)	(.067)	(.629)
Age (Ref: Under 64)	4.763***	4.764***	.157	.161	5.862***	5.875***	6.097***	6.111***	5.966***	5.987***
	(.325)	(.324)	(.145)	(.145)	(.369)	(.386)	(.369)	(.386)	(.389)	(.406)
Interaction term										
Social capital index*Age		-.544*		.154		.079		.081		.137
		(.278)		(.151)		(.606)		(.600)		(.632)
Socioeconomic status index (Ref: Middle SES)										
Lower SES	1.079*	1.079*	.291	.291	.350***	.350***	.367***	.367***	.385*	.386*
	(.489)	(.489)	(.237)	(.237)	(.053)	(.053)	(.054)	(.054)	(.178)	(.178)
Higher SES	-.254	-.254	-.651**	-.651**	-.080	-.080	-.006	-.006	-.309 +	-.309 +
	(.453)	(.453)	(.205)	(.205)	(.058)	(.058)	(.060)	(.060)	(.164)	(.163)
Population density (log)	.302*	.302*	.668***	.668***	.076***	.076***	-.003	-.003	.160**	.160**
	(.145)	(.145)	(.077)	(.077)	(.017)	(.017)	(.018)	(.018)	(.055)	(.055)
Proportion 65 years and older	-.066	-.066	.106	.099	-.169	-.169	-.317	-.317	.333	.339
	(2.376)	(2.376)	(1.058)	(1.059)	(.285)	(.285)	(.330)	(.330)	(1.097)	(1.098)
Proportion of women in the population	.480	.480	2.424	2.456	1.227 +	1.227 +	−1.599*	−1.599*	.228	.224
	(6.087)	(6.087)	(2.638)	(2.642)	(.691)	(.691)	(.779)	(.779)	(2.333)	(2.332)
Proportion of single-person househlds	3.338 +	3.338 +	1.442 +	1.449 +	1.785***	1.785***	1.619***	1.619***	2.567***	2.564***
	(1.891)	(1.88)	(.814)	(.815)	(.230)	(.230)	(.259)	(.259)	(.739)	(.739)
Residential stability	3.633 +	3.633 +	1.889*	1.896*	1.758***	1.758***	1.471***	1.471***	2.309*	2.305*
	(2.176)	(2.173)	(.930)	(.931)	(.323)	(.313)	(.386)	(.386)	(.954)	(.955)
Tsunami height (m)	.315***	.315***	.151***	.151***	.108***	.108***	.082***	.082***	.146***	.146***
	(.040)	(.040)	(.020)	(.021)	(.004)	(.004)	(.004)	(.004)	(.017)	(.017)
Area of the community (km2)	-.003	-.003	.088***	.089***	-.003*	-.003*	-.004**	-.004**	-.003	-.003
	(.005)	(.005)	(.025)	(.025)	(.001)	(.001)	(.001)	(.001)	(.002)	(.002)
Coast line length (km)	-.099*	-.099*	.112*	.011*	-.033***	-.033***	-.047***	-.047***	-.025	-.025
	(.042)	(.042)	(.048)	(.048)	(.006)	(.006)	(.007)	(.007)	(.016)	(.016)
Distance between sea and nearest mountain (km)	.851***	.851***	.345***	.345***	.293***	.293***	.238***	.238***	.404***	.404***
	(.130)	(.130)	(.070)	(.070)	(.012)	(.012)	(.013)	(.013)	(.057)	(.057)
Seawall height (m)	-.067	-.067	-.075**	-.075**	-.030***	-.030***	-.010	-.010	-.011	-.011
	(.061)	(.061)	(.028)	(.028)	(.008)	(.008)	(.009)	(.009)	(.026)	(.026)
Designated city dummy (Ref: No)	−4.116***	−4.116***	−1.375*	−1.376*	−1.412***	−1.412***	−1.196***	−1.196***	−2.072***	−2.070***
	(1.154)	(1.153)	(.559)	(.559)	(.128)	(.128)	(.135)	(.135)	(.498)	(.498)
Constant	−7.454*	−7.454*	−7.806***	−7.831***	−8.297***	−8.310***	−5.790***	−5.804***	−9.721***	−9.737***
	(3.569)	(3.564)	(1.589)	(1.591)	(.588)	(.599)	(.644)	(.654)	(1.417)	(1.421)
	(3.569)	(3.564)	(1.589)	(1.591)	(.588)	(.599)	(.644)	(.654)	(1.417)	(1.421)
Tsunami height (m)							-.091***	-.091***		
							(.022)	(.022)		
Constant							−1.004***	−1.004***		
							(.156)	(.156)		
Log α									.575	.575
									(.076)	(.076)
									1.776	1.777
									(.135)	(.135)
R2/Pseudo R2	.224	.226	.176	.176	.486	.486			.230	.230

Notes: Numbers in parentheses are standard errors. N = 1084.
+ p < .10, *p < .05, **p < .01, ***p < .001.

Poisson regression. Thus, we only need to focus on the coefficient of interaction term in OLS model.

In the OLS regression, the significance of the effect of social capital index disappears when the interaction term is included. This means that the effect of social capital exists primarily among elderly people but not among younger people. The coefficient of the interaction term is −0.54 indicating that, holding other factors constant, if social capital in the increases one unit, the disaster-related mortality of 65 and older people will decrease 0.54 percentage.

Furthermore, as mentioned previously, we verify the difference of the coefficients for the social capital index in three ways. The results displayed in Table 3 come from the stacking method, while the results of the seemingly unrelated regression (SU) modeling and T-test and Structural equation (SEM) - which confirm the stacking approach - are available upon request.

5. Discussion

This paper has moved beyond of the challenges encountered by past research on Japan's 3.11 tsunami, such as studies which "could not address the reasons for the observed mortality patterns and regional differences" (Nakahara & Ichikawa, 2013). We have used a variety of model types to investigate the relationship between social capital, age, and socioeconomic status (SES), focusing on the interactions between proxies for vulnerability and social ties. As scholars have argued, "an integrated vulnerability and social capital framework has much merit" (Durant, 2011). Rather than seeing social ties solely in terms of simple binary outcomes - such as social capital uniformly assisting all cohorts, or all lower SES groups facing similar levels of morbidity - our community level results paint a different and more nuanced picture. We found social ties did the most for the elderly and communities with fewer material and educational resources.

Our approach, like all quantitative investigations, has a number of limitations. First, as we have used the *machi ōaza* (neighborhood) level of analysis, we are unable to comment on individual level behaviors or mortality outcomes due to the ecological inference problem (see King, 1997 for a nuanced discussion of this challenge). It may be that health experts, disaster managers, and residents regularly engage in policies and interventions at the individual, and not neighborhood level. Fortunately, much past work on social science and disasters uses epidemiological approaches which rest at the community, and not the individual, level (cf Kobayashi, Suzuki, Kawachi, & Takao, 2015).

Next, as we have had to rely on publicly available datasets in an observational study, we have likely introduced bias into our coefficients through endogeneity because of our inability to carry out a randomized control trial. One solution for future work on mortality and crisis might be to incorporate coarsened exact matching (CEM) techniques which seek to overcome this challenge through technical means (Iacus, King, & Porro, 2012).

Notwithstanding any shortcomings, this analysis uncovers two important findings that provide a more balanced perspective on the role of social ties during disaster. First, social capital's influence on mortality was highest in communities with low socioeconomic status. Less educated and poorer neighborhoods saw the strongest benefits from social capital during the tsunami. Conversely, communities with much higher educated and wealthier residents did not see mortality levels drop due to higher levels of social cohesion, community facilities, and NGOs. Further, social capital's effect on mortality was only visible among the elderly. People over the age of 65 with higher levels of social capital had lower mortality rates than other elderly with fewer ties. Younger people did not see these effects from community engagement and deeper reservoirs of social capital.

Our findings reinforce past research that has argued that certain types of social ties can do more than just help the poor “get by” - here it literally saved lives, providing group mobilization and collective action for those facing the tsunami. The differences between the way that social capital interacted with low, middle and high SES levels calls for further reflection. In wealthier and better educated communities it may be that neighbors had fewer reasons pre-tsunami to work together and to build social ties. Those better off neighborhoods may have had fewer external stressors - such as marginalization, economic precarity, or immobility - that pushed lower SES communities to help each out before the tsunami arrived. Poorer communities may have engaged more in gift giving, engagement with public facilities and third spaces, and participation in horizontal associations. As studies of the 1995 Kobe earthquake showed, poor and middle class communities that had built group ties before the disaster arrived demonstrated the ability to work as a group under stress when the earthquake and resulting fires struck (Yasui, 2007).

5.1. Policy recommendations

Aging and its consequences may naturally reduce the social infrastructure available to the elderly. So too society - with discrimination, restrictive zoning measures, and expectations of education - may create unhealthy environments in communities with low SES. Our study brings good news for both of these vulnerable populations: social ties can help them survive a massive catastrophe. This study of more than 500 neighborhoods reinforces the qualitative descriptions of how neighbors saved neighbors in the first 40 min after Japan's 3/11 earthquake (Takezawa, 2016). Several policy recommendations follow from our findings.

First, disaster managers and local decision makers should at least not negatively impact social ties by moving individuals randomly into post-disaster temporary housing. Studies of Tohoku survivors, some of whom were relocated randomly while others were relocated a group, showed that group relocation helped maintain social ties (Hikichi, Sawada, Tsuboya, Aid, Kondo, Koyama, and Kwachi 2017). Whenever possible, municipal and local decision makers should seek to keep communities and neighborhoods united during the evacuation and rehousing phases.

Next, rather than seeking to mitigate future disasters by over investing in physical infrastructure systems such as dams and seawalls - which, in this study, had no measurable impact on reducing mortality - local, regional, and national governments should assist local communities in creating and maintaining social ties. Japan already has a number of local programs, including the Hamarassen, Ibasho, and Onagawa community currency programs all of which seek to create social connections for the elderly and to enhance their resilience to shocks.

Finally, we hope our investigation into the interaction between social capital and vulnerability at a neighborhood level will help spur on future quantitative and qualitative research on resilience and survival. Given the likelihood of an increase in extreme weather events, researchers should prioritize investigations which will help societies better mitigate and prepare for future shocks.

Ethics approval

This paper has not been submitted to any other journals nor published previously.

Declarations of interest

None.

IRB/human subjects licensing

Not applicable (no individuals or individual data studied in this paper).

Permissions

None necessary (all datasets and figures products of the authors).

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Appendix

Table 1
Dataset Sources

Variables	Source
Tsunami mortality (including under 64, 65 years and older)	2012, Kenji TANI, Distribution of the number of deaths and the death rate on the Great East Japan Earthquake (http://ktgis.net/tohoku_data/small_area_map/)
NPO number	Cabinet Office, Government of Japan (https://www.npo-homepage.go.jp/npoportal/)
Kominkan number	National Land Numerical Information, Japan (http://nlftp.mlit.go.jp/ksj/index.html)

(*continued on next page*)

Table 1 (*continued*)

Variables	Source
Public facility number	National Land Numerical Information, Japan (http://nlftp.mlit.go.jp/ksj/index.html)
Proportion of education degree, occupation and industry	Statistics Burau, Ministry of Internal Affairs and Communications (https://www.e-stat.go.jp/stat-search/files?page=1&toukei=00200521)
Population	Statistics Burau, Ministry of Internal Affairs and Communications (https://www.e-stat.go.jp/stat-search/files?page=1&toukei=00200521)
Proportion of women, 65 years and older in the population	Statistics Burau, Ministry of Internal Affairs and Communications (https://www.e-stat.go.jp/stat-search/files?page=1&toukei=00200521)
Single-person households proportion	Statistics Burau, Ministry of Internal Affairs and Communications (https://www.e-stat.go.jp/stat-search/files?page=1&toukei=00200521)
Residential stability	Statistics Burau, Ministry of Internal Affairs and Communications (https://www.e-stat.go.jp/stat-search/files?page=1&toukei=00200521)
Tsunami height	The 2011 Tohoku Earthquake Tsunami Joint Survey (TTJS) Group (http://www.coastal.jp/ttjt/index.php)
Area of the communities	Statistics Burau, Ministry of Internal Affairs and Communications (https://www.e-stat.go.jp/gis)
Coastal line length	National Land Numerical Information, Japan (http://nlftp.mlit.go.jp/ksj/index.html)
Distance between sea and nearest mountain	Geospatial Information Authority of Japan (GSI) (http://www.gsi.go.jp/ENGLISH/)
Sea wall height	Ministry of Land, Infrastructure, Transport and Tourism (http://www.thr.mlit.go.jp/)

Table 2
List of Cities, Towns, and Villages in the Dataset

Fudai
Futaba
Higashimatsushima
Hirono
Ishinomaki
Iwaizumi
Iwaki
Iwanuma
Kamaishi
Kesennuma
Kuji
Matsushima
Minamisanriku
Minamisoma
Miyagino
Miyako
Namie
Naraha
Natori
Noda
Ofunato
Okuma
Onagawa
Otsuchi
Rifu
Rikuzentakata
Shichigahama
Shinchi
Shiogama
Soma
Tagajo
Taihaku
Tanohata
Tomioka
Wakabayashi
Watari
Yamamoto
Yamada

The equation of the "stacking" method can be written as follows.

$$y_{Under\ 64\ Mortality} = \beta_{10} + \beta_{11} S.\ C. + \boldsymbol{\beta}_{1C.V.} \boldsymbol{C.\ V.} + \varepsilon_1 \tag{1}$$

Equation (1) expresses the equation for the mortality regression on communities whose age was under 64. $S.\ C.$ represents the social capital variable while $C.\ V.$ represents the vector of control variables, and β_{11} and $\beta_{1C.V.}$ represent their coefficients respectively.

$$y_{Over\ 65\ Mortality} = \beta_{20} + \beta_{21} S.\ C. + \boldsymbol{\beta}_{2C.V.} \boldsymbol{C.\ V.} + \varepsilon_2 \tag{2}$$

Equation (2) expresses the equation of the 65 and older mortality regression. Here, we seek to compare the two coefficients β_{11} and to test if they are different and to test the significance of the difference. Therefore, we stack those two datasets and build a third equation which includes the interaction term between social capital index and age.

$$y_{Total\ Mortality} = \beta_{30} + \beta_{31}S.\ C. + \beta_{32}Age + \beta_{33}S.\ C. * Age + \boldsymbol{\beta}_{1C.V.}\boldsymbol{C.\ V.} + \varepsilon_3 \quad (3)$$

Equation (3) represents the regression equation for the stacking method. In this equation, *Age* is the binomial variable created by stacking to distinguish the two age categories, and β_{32} represents the average difference of the mortality between people under 64 and 65 and older. The $S.\ C. * Age$ represents the interaction term between social capital and age. The β_{33} is the coefficient of the interaction term and also the difference of the effect of social capital between people under 64 and people 65 and older. The P value of β_{33} tests the significance of the difference.

Additional note: We also utilized the k-mean clustering method to check the robustness of our clusters and we discovered similar clusters to those created by the hierarchical cluster method.

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