Substitute or Complement? How Social Capital, Age and Socioeconomic Status Interacted to Impact Mortality in Japan's 3/11 Tsunami

Maoxin Ye and Daniel P. Aldrich

Abstract: Much research has underscored the critical nature of social capital during crises. Yet we have less information on how social ties interact with vulnerability factors such as age and socioeconomic status to influence mortality of the most vulnerable. Using a new, micro-level dataset of all 550 inundated neighborhoods from nearly 40 cities, towns, and villages across Japan's Tohoku region, we analyze the factors that influenced mortality during the 11 March 2011 tsunami at the community level. 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. For the elderly and those with lower socioeconomic status, *ceteris paribus*, deeper reservoirs of social capital are linked with lower levels of mortality. These findings bring with them important policy implications for disaster managers, communities, and decision makers facing the crisis.

Keywords: social capital, vulnerability, tsunami, mortality, disaster, socioeconomic status, age

Introduction

At 2:46 pm on 11 March 2011 a massive, 9.0 magnitude earthquake struck off Japan's northeast region. That earthquake then set off a series of tsunami that 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 and caused a nuclear meltdown at the Fukushima Dai-ichi plants. 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 minutes 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. 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 and Ichikawa 2013).

Vulnerable residents without neighbors, friends, or family to act as rescuers were at higher risk of death (Muir-Wood 2016: 198). In active and engaged communities, however, neighbors, volunteer firefighters, friends, and family members entered the homes and hospital rooms of those in danger to warn and rescue them. In some cases of pro-social behavior this involved carrying the vulnerable on their backs, putting them on the backs of mopeds, or giving them a ride in a car or van to a safer location (Branigan 2015; Author interviews 2018). 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).

We use a new dataset on more than 550 neighborhoods across nearly 40 cities, towns, and villages in Tohoku to study the factors at the community level which influenced mortality during the tsunami. Our analysis uncovers two important findings that provide a more nuanced 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 ties during the tsunami. Conversely, communities with better 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 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 and Sawada 2015; Nateghi, Bricker, Guikema and Bessho 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 (Patterson, Weil, and Patel 2009).

Next, where some studies of disasters have focused primarily on the role of social ties, 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, Rahbar, Lee, Chen, Alam, Pope and Adams 2013). This builds on a growing recognition of the importance of taking income, education, and age-related factors into account in disaster research (Fothergill and 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 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 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, communities would be at greater risk from a hazard like a tsunami.

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, and 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, Hikichi, Matsuyama, Sato, Tsuboya, Tabuchi, Koyama, Subramanian, Kondo, Osaka, and Kawachi 2017). Stepping beyond this simple binary disagreement, we find 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.

Theory

We build our study on past research which has highlighted the importance of a number of factors, including social capital, age, and socioeconomic status alongside control variables for the geographic and administrative environment, that may influence mortality during disasters.

Much research has illuminated the role of **social capital** and social cohesion during crises (Buckland and Rahman 1999; Dynes 2005; Aldrich 2012). We follow a standard approach to defining social capital as "the features of social organizations, such as networks, norms, and trust, that facilitate action and cooperation for mutual benefit" (Putnam 1993: 35). Social ties 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 and Woolcock 2004).

Social ties have proven important during crises for a number of reasons. Such connections provide information, resources, and moral support at critical junctures (Hurlbert, Haines, and Beggs 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 and Shaw 2004). As we discuss below, we use several indicators of social tie tied together in an index to take into account participation in voluntary groups along with social infrastructure levels.

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 and Thomas 2014). Focusing on age is important as Japan's greying problem is more critical than in other countries, especially in the periphery (Muramatsu and Akiyama 2011). In these coastal communities in Tohoku, the mean age is higher than the national average, and there are far more elderly than young residents. 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 to 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.

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 and Hanratty 2012). This kind of isolation leads to higher mortality during non-crisis times compared to that of younger people (Seeman et al. 1987); *a fortiori* elderly who are isolated during disasters may face higher risks. The elderly are more likely to report fewer social ties than younger respondents 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 (**hereafter SES**)**. We do so for a number of reasons. It is likely that the quality of infrastructure - such 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. Finally, as communities' income rises, inequality increases, and past studies have shown increasing base mortality rates correlating with inequality (Kawachi et al. 1997).

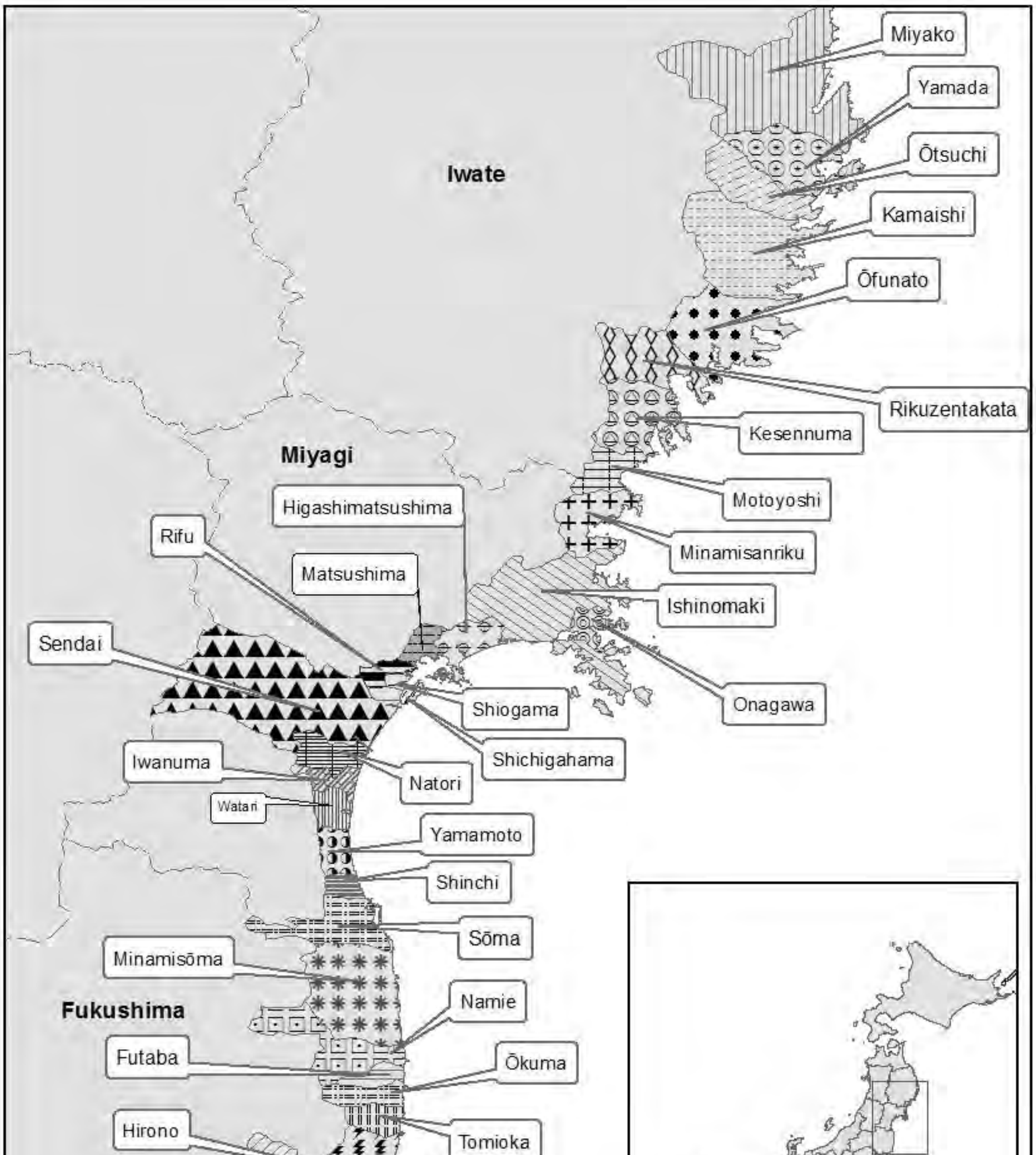
Recognizing that SES may affect mortality differently depending on the presence or absence of trust and cooperation, we seek to understand the *interaction between social capital and SES* because of conflicting findings from past studies. Some have argued that SES and levels of social capital are correlated so that poorer communities have less engagement, trust, and cohesion (Subramian, Lochner and Kawachi 2003; Han et al. 2014). This may be because poorer communities with less education may 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. When handling economic stress, including being an unskilled worker, lacking effective health insurance, and requiring sick leave impact the health and wellbeing even in relatively egalitarian societies, social infrastructure may mitigate some of those impacts (Lindstrom, Rosvall, and Lindstrom 2017). Communities with lower levels of SES would 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, and Boyce 2010). Our paper can help shed light on this question.

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, can account for differences in mortality due to inundation variation (Ishiguro and 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, Bricker, Guikema, and Bessho 2016), although others have found little evidence for these claims (Aldrich and Sawada 2015). We now look to explain the data and methods used in our analysis.

Data and Methods

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 more than 550 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. Figure 1 illustrates the geographic region of Japan under study here

Figure 1: Coastal area under study



Rather than serving as a partial sample, our dataset encompasses all registered, inundated neighborhoods in the Tohoku region. Hence no weighting or reweighting is necessary should we wish to extrapolate broader trends from our dataset which is the full universe of cases of community level exposure to the hazard.

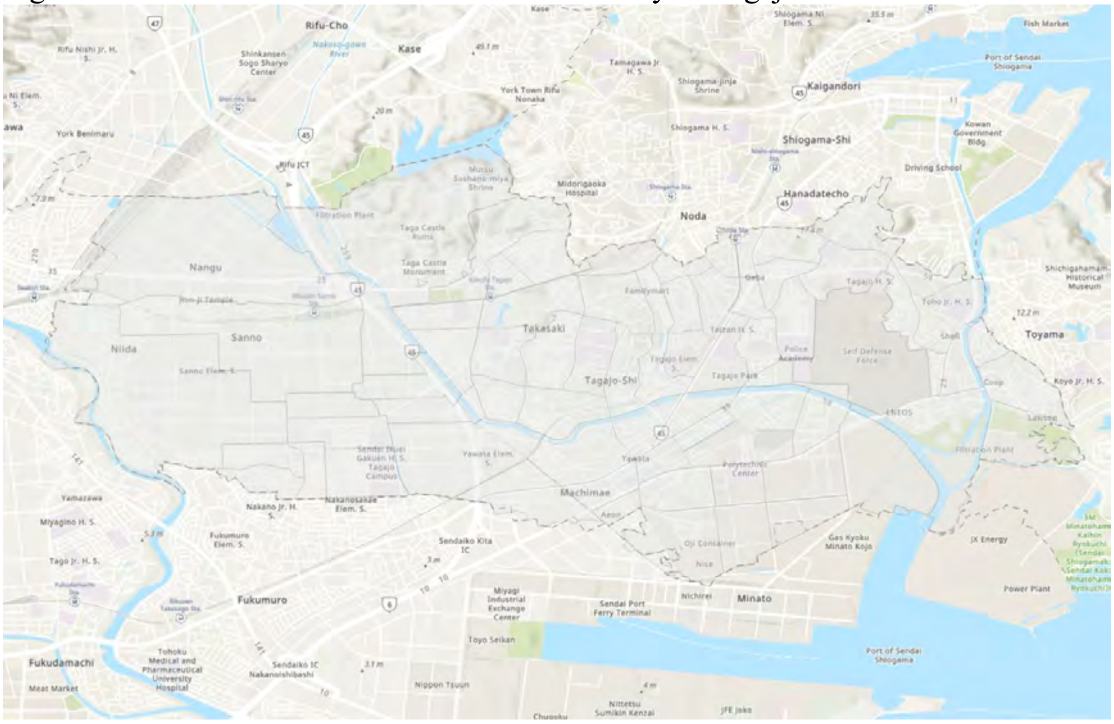
A full list of the sources for our variables can be found in Appendix Table 1 and a list of the cities, towns, and villages from which we drew our sample can be found in Appendix Table 2. This study uses the neighborhood (*machi ōaza* in Japanese) as its level of analysis, with each geographic unit holding an average population of approximately 1,364 people and a mean area of 42.63 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 1,500 people per block, although of course, many blocks in North America have no population).

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, Kondo, Hirai, Subramanian, Murata, Kondo, Ichida, Shirai and Osaka 2010). 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 and 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, and Imamura 2017).

Because our unit of analysis sits at the neighborhood level, we can also better capture a critical independent variable for our study, namely social capital. As social capital remains a relatively abstract conception it can be challenging to measure it 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: 1).

In order to visualize the advantages of this level of analysis, we provide an example of neighborhoods in the city of Tajago in Miyagi Prefecture in Figure 2. The grey overlaid areas sectioned off by thin black lines are each a neighborhood for our analysis.

Figure 2: *Machi ōaza* -level communities in the city of Tagajo



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. For a more detailed analysis of the interaction between age, SES, and social capital, we focus further in on the normed mortality rate of the elderly. Not every inundated neighborhood in Tohoku experienced tsunami-related elderly deaths. Out of the 561 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 in the city of Soma).

Independent Variables

Social Capital

Our core variable of interest 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 et al. 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 (Kanaya 2008; Kusakabe 2014; Sakurai 2007; Tanaka 2007).

Along with NPO density, we capture the number of cultural centers in the community per 1000 people as another measure of social capital (cf. Ogino 2014). These facilities help residents meet, engage in mutual teaching and learning (Ministry of Education 2008) and create social capital among (Glover 2004). Additionally, in fact, another study in Japan indicated that *Kōminkan* can help 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 and 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 et al. 2010; Ferguson 2012; Svendsen 2013), while gyms enhance the friendship and trust among the citizens through the team sports (Elmose-Østerlund and van der Roest 2017; Marlier et al. 2015; Skinner et al. 2008). Public gardens offer a communal place for citizens' daily life helping to promote communication as a third space (Alaimo et al. 2010).

Socioeconomic Status

This study employs three proxies to capture the socioeconomic status across our communities: education level, occupation, and industry. We categorize education into junior high school, high school, junior and technical college, college and university degree. We include management, professional, official and general occupations for employment and divide industry into first, second and third 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 higher primary school educated, general-occupational and first-industrial residents. Middle SES communities have higher proportions of high school educated and second-industrial workers. Higher SES communities hold a higher proportion of college / university educated, managemental, professional and official-occupational residents.

Control Variables

Geographic and physical infrastructure along with broader demographic conditions may alter mortality outcomes at the neighborhood level. Following past studies (Browning et al. 2006; Aldrich and Sawada 2015), 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 place 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 controls for the influence of Sendai city communities as Sendai serves the central city of Tohoku Region by mandate of the government. Communities within it may have different mitigation infrastructure or demographics than elsewhere. We measure distance between the water and higher ground as a shorter distance between the sea and the nearest mountain enables people to evacuate to higher ground more quickly and thus increase the likelihood of survival. The descriptive statistics of all the variables are shown in Table 1.

[Table 1 here: Table 1 The Descriptive Statistics of Variables]

Variables	N	Mean/Percentage	Standard Deviation	Min	Max
Dependent Variable					
Tsunami mortality (proportion of dead in inundated areas)	561	2.325	3.853	.000	38.410
Under 64 tsunami mortality (proportion of dead whose age are under 64 in inundated areas)	561	.013	.026	.000	.290
65 and older tsunami mortality (proportion of dead whose age are 65 and older in inundated areas)	561	4.629	7.805	.000	80.000
Independent Variables					
Social capital (index)	561	.000	1.169	-.517	14.371
NPO number per 1000 people	561	.252	.991	.000	11.905
Kominkan number per 1000 people	561	1.434	3.968	.000	45.455
Public facility number per 1000 people	561	.414	1.427	.000	20.000
Demographic variables					
Socioeconomic status	561				
Lower SES	132	23.530		.000	1.000
Middle SES	187	33.330		.000	1.000
Higher SES	242	43.140		.000	1.000
Population density (log)	561	4.083	1.807	.085	10.128
Proportion 65 years and older	561	.305	.094	.041	.854
Proportion of women in the population	561	.518	.031	.364	.617
Proportion of single-person households	561	.228	.122	.000	.854
Residential stability (Proportion of people who lives in the same neighborhood from 5 years ago)	561	.841	.113	.097	1.000
Geographic variables					
Tsunami height (m)	561	6.451	5.107	.080	22.769
Area of the community (square km)	561	42.638	120.030	.008	1344.779
Coast line length (km)	561	2.130	4.447	.000	41.480
Distance between sea and nearest mountain (km)	561	1.407	1.839	.000	11.100
Seawall height (m)	561	6.905	2.811	.000	15.500
Administrative variables					
Designated city dummy	561				
No = 0	540	96.260		.000	1.000
yes = 1	21	3.740		.000	1.000

Analysis

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).

Coefficient comparison

Our core analysis of the variables requires us going beyond our basic models. Because we seek to understand the potential varying effect of social capital on the mortality of young and old, 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 cohorts. Given that we are working at the community, and not individual level, 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 1122) 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 as the original dataset 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, as the second stage of the stacking method, we combine these two datasets into one and create a binomial variable named *Age* to distinguish the mortality between 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 outcome of interest here is the significance of the difference between the coefficients of the two age categories.

While stacking is the simplest analytically, given its relatively unorthodox approach, we also carried out a second analysis using the seemingly unrelated (SU) modeling and T-test approach (Haberman and 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 and Chan 2011) 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). All three quantitative models yielded similar outcomes.

Results

Table 2 Social Capital and SES Results

	Model 1		Model 2		Model 3		Model 4		Model 5	
	OLS		Logit		Poisson		ZIP		Negative Binomial	
Social capital index	-.261*	-.022	-.313**	-.185	-.247***	-.023	-.268***	.025	-.208**	-.023
	(.131)	(.355)	(.110)	(.245)	(.043)	(.068)	(.047)	(.071)	(.069)	(.121)
Socioeconomic status (Ref: Middle SES)										
Lower SES	1.383**	1.362**	.601+	.594	.422***	.308***	.396***	.255**	.423**	.339*
	(.435)	(.435)	(.362)	(.368)	(.073)	(.077)	(.077)	(.080)	(.160)	(.162)
Higher SES	-.317	-.344	-.345	-.360	-.132	-.136	-.126	-.144	-.223	-.242
	(.408)	(.410)	(.304)	(.306)	(.084)	(.085)	(.088)	(.089)	(.153)	(.153)
Interaction term										
Social capital index*Lower SES		-.682+		-.394		-.563***		-.702***		-.644***
		(.413)		(.341)		(.108)		(.114)		(.202)
Social capital index*Higher SES		-.005		-.038		-.066		-.128		-.113
		(.397)		(.289)		(.093)		(.097)		(.156)
Population density (log)	.302*	.312**	.412***	.413***	.082***	.078***	.070**	.065*	.115*	.116*
	(.120)	(.120)	(.107)	(.107)	(.023)	(.023)	(.025)	(.025)	(.048)	(.048)
Proportion 65 years and older	1.275	2.033	-1.245	-1.000	.374	.645+	1.094*	1.601***	1.502	2.142*
	(2.126)	(2.142)	(1.605)	(1.647)	(.388)	(.391)	(.436)	(.438)	(.973)	(.994)
Proportion of women in the population	3.450	3.063	7.968	8.007+	2.499*	2.418*	.411	-.165	1.047	(-.141)
	(5.530)	(5.537)	(4.125)	(4.219)	(1.000)	(.980)	(1.198)	(1.158)	(2.222)	(2.272)
Proportion of single-personousehlds	2.082	2.074	2.599*	2.604*	1.475***	1.459***	1.414***	1.442***	2.106**	2.097**
	(1.706)	(1.701)	(1.289)	(1.297)	(.340)	(.337)	(.360)	(.355)	(.682)	(.680)
Residential stability	3.939*	3.947*	1.723	1.682	2.367***	2.282***	2.432***	2.354***	2.554**	2.327**
	(1.946)	(1.941)	(1.376)	(1.377)	(.467)	(.465)	(.501)	(.504)	(.860)	(.858)
Tsunami height (m)	.299***	.301***	.145***	.151***	.104***	.105***	.097***	.098***	.128***	.132***
	(.035)	(.035)	(.031)	(.032)	(.006)	(.006)	(.006)	(.006)	(.014)	(.015)
Area of the community (km2)	-.000	-.000	.010*	.010*	-.000	-.000	-.000	-.000	-.000	-.000
	(.000)	(.000)	(.004)	(.004)	(.000)	(.000)	(.000)	(.000)	(.000)	.000
Coast line length (km)	-.104**	-.101**	.078	.080	-.036***	-.033***	-.042***	-.039***	-.029+	-.030*
	(.038)	(.038)	(.077)	(.078)	(.008)	(.008)	(.009)	(.009)	(.015)	(.015)
Distance between sea and nearest mountain (km)	.817***	.825***	.301**	.306**	.291***	.294***	.290***	.294***	.379***	.378***
	(.117)	(.117)	(.110)	(.110)	(.018)	(.018)	(.018)	(.018)	(.051)	(.051)
Seawall height (m)	-.044	-.063	-.105*	-.111*	-.018	-.023+	-.011	-.017	-.001	-.009
	(.056)	(.056)	(.044)	(.044)	(.012)	(.012)	(.013)	(.013)	(.024)	(.024)
Designated city dummy (Ref: No)	-4.083***	-4.027***	-.873	-.860	-1.47***	-1.437***	-1.550***	-1.509***	-2.056***	-1.983***
	(1.051)	(1.047)	(.902)	(.900)	(.187)	(.188)	(.191)	(.192)	(.468)	(.463)
Constant	-7.425*	-7.373*	-7.032**	-7.069**	-4.328***	-4.226***	-3.345***	-3.052***	-4.745***	-4.081**
	(3.235)	(3.242)	(2.398)	(2.430)	(.677)	(.674)	(.753)	(.740)	(1.307)	(1.324)
Tsunami height (m)							-.035	-.032		
							(.043)	(.041)		
Constant							-2.175***	-2.182***		
							(.401)	(.393)		
Log α									.148	.122
									(.093)	(.094)
α									1.159	1.129
									(.108)	(.106)
R2/Pseudo R2	.192	.198	.156	.159	.199	.209			.075	.080

Notes: Numbers in parentheses are standard errors. N = 561.

\+ p < .10, * p < .05, ** p < .01, *** p < .001

We further divide the results of the five regression models into two columns as seen in Table 2. The left column displays the main effect of social capital and SES on tsunami mortality. The right column each model output adds an additional interaction term between social capital and SES.

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 during shocks (Aldrich and Sawada 2015). In the OLS regression model, for example, the estimated coefficient for the social capital index is -0.26, meaning if the social capital index in the communities increases one unit, the disaster-related mortality will decrease 0.26 holding all other variables in the model constant.

Setting the middle SES communities as the reference variable, we see that that only lower SES is positively and significantly associated with the mortality. That is, compared with middle SES neighborhoods, tsunami mortality is higher in the lower SES communities. These findings fit with arguments about lower quality of buildings and residences along with comparatively fewer warning systems in such neighborhoods. The coefficient in the OLS regression, for example, is 1.383, demonstrating that the average mortality in lower communities is 1.383 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 -0.682, meaning that if social capital in the lower SES communities increases one unit, the disaster-related mortality will decrease 0.682 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.

Table 3 Social Capital and Age Results

	Model 4		Model 5		Model 6		Model 7		Model 8	
	OLS		Logit		Poisson		ZIP		Negative Binomial	
Social capital index	-.249+	.013	-.304***	-.389***	-.235***	-.315	-.199***	-.286	-.189**	-.330
	(.141)	(.195)	(.078)	(.117)	(.030)	(.603)	(.036)	(.597)	(.067)	(.630)
Age (Ref: Under 64)	4.616***	4.616***	.136	.141	5.858***	5.872***	6.091***	6.106***	5.967***	5.989***
	(.315)	(.315)	(.139)	(.140)	(.368)	(.385)	(.368)	(.385)	(.388)	(.405)
Interaction term										
Social capital index*Age		-.524*		.156		.080		.087		.143
		(.269)		(.150)		(.603)		(.597)		(.632)
Socioeconomic status (Ref: Middle SES)										
Lower SES	1.010*	1.010*	.127	.126	.327***	.327***	.365***	.365***	.341+	.342+
	(.469)	(.468)	(.222)	(.222)	(.053)	(.053)	(.054)	(.054)	(.177)	(.177)
Higher SES	-.184	-.184	-.408*	-.407*	-.067	-.067	-.021	-.021	-.345+	-.330
	(.440)	(.439)	(.195)	(.196)	(.058)	(.058)	(.061)	(.061)	(.162)	(.630)
Population density (log)	.237+	.237+	.436***	.436***	.060***	.060***	.003	.003	.134*	.134*
	(.130)	(.129)	(.067)	(.067)	(.016)	(.016)	(.018)	(.018)	(.054)	(.054)
Proportion 65 years and older	-.072	-.072	-.347	-.351	-.134	-.134	-.226	-.226	.328	.333
	(2.289)	(2.286)	(1.011)	(1.011)	(.283)	(.283)	(.327)	(.327)	(1.079)	(1.080)
Proportion of women in the population	.499	.499	4.125	4.147	1.282+	1.282+	-1.751*	-1.750*	.517	.513
	(5.854)	(5.946)	(2.586)	(2.588)	(.691)	(.691)	(.790)	(.790)	(2.343)	(2.343)
Proportion of single-person househlds	3.297+	3.297+	1.489+	1.493+	1.825***	1.825***	1.665***	1.665***	2.612***	2.610***
	(1.837)	(1.834)	(.796)	(.797)	(.229)	(.229)	(.260)	(.260)	(.738)	(.738)
Residential stability	3.346	3.346	1.411	1.416	1.685***	1.685***	1.385***	1.385***	2.147*	2.143*
	(2.095)	(2.092)	(.898)	(.797)	(.310)	(.310)	(.387)	(.387)	(.941)	(.941)
Tsunami height (m)	.317***	.317***	.128***	.128***	.112***	.112***	.088***	.088***	.152***	.152***
	(.038)	(.038)	(.019)	(.019)	(.004)	(.004)	(.004)	(.004)	(.017)	(.017)
Area of the community (km2)	-.000	-.000	.007***	.007***	-.000*	-.000*	-.000***	-.000***	-.000	-.000
	(.000)	(.000)	(.002)	(.002)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Coast line length (km)	-.102*	-.102*	.107*	.106*	-.034***	-.034***	-.047***	-.047***	-.026	-.026
	(.041)	(.041)	(.045)	(.045)	(.006)	(.006)	(.007)	(.007)	(.016)	(.016)
Distance between sea and nearest mountain (km)	.837***	.837***	.332***	.332***	.297***	.297***	.245***	.245***	.405***	.405***
	(.126)	(.126)	(.068)	(.068)	(.013)	(.013)	(.013)	(.013)	(.056)	(.056)
Seawall height (m)	-.071	-.071	-.085**	-.086**	-.029***	-.029***	-.006	-.006	-.008	-.008
	(.060)	(.060)	(.028)	(.028)	(.008)	(.008)	(.009)	(.009)	(.026)	(.026)
Designated city dummy (Ref: No)	-4.018***	-4.018***	-1.414**	-1.415**	-1.413***	-1.413***	-1.186***	-1.186***	-2.062***	-2.060***
	(1.132)	(1.130)	(.548)	(.548)	(.128)	(.128)	(.136)	(.136)	(.496)	(.495)
Constant	-7.251*	-7.252*	-5.483***	-5.504***	-8.100***	-8.115***	-5.798***	-5.813***	-9.341***	-9.357***
	(3.487)	(3.483)	(1.531)	(1.533)	(.588)	(.599)	(.648)	(.657)	(1.412)	(1.415)
Tsunami height (m)							-.083***	-.083***		
							(.021)	(.021)		
Constant							-1.085***	-1.085***		
							(.150)	(.150)		
Log α									.579	.579
									(.075)	(.075)
α									1.785	1.785
									(.134)	(.134)
R2/Pseudo R2	.222	.224	.146	.146	.487	.487			.231	.232

Notes: Numbers in parentheses are standard errors. N =1122.
+ p < .10, * p < .05, ** p < .01, *** p < .001

Now, turning to Table 3, 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 4.616, means the average mortality among 65 and older people is 4.616 percentage points higher than that among people under 64.

We focus our results on 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 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 -0.524 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 0.524 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.

Discussion

We have used a variety of model types to investigate the relationship between social capital, age, and socioeconomic status, 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 breaking down along 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 picture. We found social ties had the most beneficial outcomes for the elderly and communities with fewer material and educational resources.

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 that disaster arrived demonstrated the ability to work as a group under stress when the earthquake and resulting fires struck (Yasui 2007).

Conclusion

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 minutes after Japan's 3/11 earthquake. 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 more 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). Where individuals were placed in new housing without friends, family or social structures they were likely to lose existing ties and also face new risks such as a lonely death (*kodokushi*).

Next, rather than seeking to mitigate future disasters by over investing in physical infrastructure systems such as dams and seawalls - which, in this study, like previous studies (Aldrich and Sawada 2015), 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 (Aldrich and Kiyota 2017).

We hope that our microlevel study of neighborhoods helps light on the critical nature of social ties and the more complex ways that this resource interacts with poverty and age. Future studies should consider moving away from city and regional investigations to ones which better capture the microlevel social interactions that define life for many urban and rural dwellers. Finally, policy makers and disaster managers should invest more heavily in creating and building social ties for those already vulnerable to shocks.

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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)
Public facility number	National Land Numerical Information, Japan (http://nlftp.mlit.go.jp/ksj/index.html)
Proportion of each education degree	Statistics Burau, Ministry of Internal Affairs and Communications (https://www.e-stat.go.jp/stat-search/files?page=1&toukei=00200521)
Proportion of each occupation	Statistics Burau, Ministry of Internal Affairs and Communications (https://www.e-stat.go.jp/stat-search/files?page=1&toukei=00200521)
Proportion of each 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 Bureau, 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/)

Appendix Table 2: List of Cities, Towns, and Villages

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

Appendix 2: Notes on Methodological Details

The equation of the "stacking" method can be written as follow.
$y_{Under\ 64\ Mortality} = \beta_{10} + \beta_{11} S.C. + \boldsymbol{\beta_{1C.V.}} \boldsymbol{C.V.} + \varepsilon_1$ (1)
Equation (1) expresses the equation for the under 64 mortality regression. $S.C.$ represents the social capital variable while $\boldsymbol{C.V.}$ represents the vector of control variables, and β_{11} and $\boldsymbol{\beta_{1C.V.}}$ represent their coefficients respectively.
$y_{Over\ 65\ Mortality} = \beta_{20} + \beta_{21} S.C. + \boldsymbol{\beta_{2C.V.}} \boldsymbol{C.V.} + \varepsilon_2$ (2)
Equation (2) expresses the equation of the 65 and older mortality regression. Here, we seek to compare the two coefficients β_{11} and β_{21} 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.
$y_{Total\ Mortality} = \beta_{30} + \beta_{31} S.C. + \beta_{32} Age + \beta_{33} S.C. * Age + \boldsymbol{\beta_{1C.V.}} \boldsymbol{C.V.} + \varepsilon_3$ (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 used similar clusters created for the hierarchical cluster method.

$y_{Under\ 64\ Mortality} = \beta_{10} + \beta_{11} S.C. + \beta_{1C.V.} \boldsymbol{C.V.} + \varepsilon_1$ (1)
$y_{Over\ 65\ Mortality} = \beta_{20} + \beta_{21} S.C. + \beta_{2C.V.} \boldsymbol{C.V.} + \varepsilon_2$ (2)
$y_{Total\ Mortality} = \beta_{30} + \beta_{31} S.C. + \beta_{32} Age + \beta_{33} S.C. * Age + \beta_{1C.V.} \boldsymbol{C.V.} + \varepsilon_3$ (3)