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Does Social Capital Mitigate Natural Disaster Risk? Evidence from Voluntary Disaster Prevention Organizations in Japan

by

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Does social capital mitigate natural disaster risk? Evidence from Voluntary Disaster Prevention Organizations in Japan

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Abstract

As climate change accelerates, the frequency and intensity of natural disasters, particularly meteorological ones, have increased. While physical capital plays a critical role in mitigating damage, it alone cannot fully address disaster risk, and recent studies find the importance of social capital. However, existing empirical studies often focus on specific disasters or regions, and national-level analyses typically rely on aggregated data that obscure local dynamics. To advance our understanding of social capital's role in disaster resilience, we constructed a novel municipality-level panel dataset that includes both natural disaster and social capital indicators across Japan. Social capital is measured by the number and annual activities of voluntary disaster prevention organizations, that is, community-led groups that conduct disaster drills and other prevention activities. Our dataset covers the years from 2014 to 2023. Using fixed-effects regression models, we find that, controlling for the severity of natural hazards, these organizations' greater presence and activity level are significantly associated with fewer casualties during storms and floods. Such a relationship is only weakly observed for earthquakes. These findings suggest that social capital is particularly important in mitigating the impacts of more predictable disasters, where community-led evacuation and coordination efforts are more feasible.

Keywords: natural disaster, flood, earthquake, social capital, Japan
JEL classification: A12, H84, Q54

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Highlight

- We constructed a novel municipality-level dataset on social capital across Japan
- Social capital is measured by the number and activity of community-led disaster groups
- Greater social capital significantly reduces human damage from floods and storms
- Such an effect is weaker for earthquakes, highlighting its role in predictable hazards

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1. Introduction

Natural disasters have long caused substantial damage to societies and economies. Recent advances in disaster risk reduction, such as infrastructure and early warning systems, have reduced damage from earthquakes, floods, and storms. Nevertheless, natural disasters result in the deaths of approximately 40,000 to 50,000 people each year and cause injuries to countless more [1]. Furthermore, climate change also increases the risk of weather-related disasters, and related damage is expected to rise.

Efforts to reduce disaster risk have traditionally focused on physical capital, including the reinforcement of buildings, the construction of flood barriers, and the development of early warning systems. However, such physical investments alone are insufficient to address all aspects of disaster risk, particularly societal vulnerability [2]. Therefore, enhancing social capital to strengthen community resilience plays a crucial role in comprehensive disaster risk reduction.

Against this backdrop, emerging empirical studies have examined the role of social capital in disaster prevention and mitigation. However, as many existing studies, particularly those using survey data, focus on specific regions or particular disasters, and their measures of social capital vary [3–7], the general relationship between disasters and social capital remains insufficiently explored. While some studies conduct national-level analyses, they used data aggregated at broad administrative units (i.e., prefectures), masking the important community-level heterogeneities and the underlying mechanisms linking social capital to disaster risk [8,9]. Hence, a more granular analysis is necessary to better understand the role of social capital in disaster risk prevention.

To address this gap, we constructed a novel dataset spanning the period from 2014 to 2023, covering all of Japan and focusing on community-level social capital, as proxied by the presence of Voluntary Disaster Prevention Organizations (VDPOs). VDPOs are community-led groups that engage in disaster drills and other preventive activities in the normal times. During disasters, they engage in guiding refugees, rescuing residents, and providing first-aid, food, and water. While existing data on VDPOs were only available at the prefecture level (N = 47), we obtained disaggregated data at the municipality level (N = 1,741) from the Fire and Disaster Management Agency (FDMA) for use in our analysis. In addition, we compiled new municipality-level data on disaster damages caused by floods/storms and earthquakes, two of the most damaging natural hazards in Japan. Over our study period, we identified 57 flood and storm events and 28 earthquake events.

Using fixed-effects regression models, we find that, controlling for the severity of natural hazards, the presence and activity levels of VDPOs are significantly associated with a reduction in the number of casualties during floods and storms. Our empirical specification includes both municipality fixed effects and disaster fixed effects, thereby accounting for time-invariant differences across municipalities in disaster preparedness or response capacity, as well as unobserved disaster-specific factors that may affect damages. Moreover, our results remain robust when we further include prefecture-by-disaster fixed effects, which control for heterogeneity in disaster responses across prefectures for each specific event.

In contrast, the mitigating effect of VDPOs is much less pronounced in the context of earthquakes. In particular, we did not find such an effect on severe earthquakes. These findings suggest that social capital plays a more prominent role in reducing damages from relatively predictable disasters like storms and floods. In such contexts, proactive measures such as community-led evacuations and coordination efforts are more feasible and likely to be effective.

While prior research has primarily investigated the role of social capital in disaster outcomes through case studies of specific events, often focusing on a single disaster or localized context, our study contributes to the literature by providing broader empirical evidence that social capital can play a generalizable role in mitigating the adverse impacts of natural disasters. In doing so, our findings not only align with but also strengthen the conclusions of earlier studies by demonstrating this relationship across a larger and more diverse set of disaster events and areas. Specifically, our result that higher levels of social capital are significantly associated with reduced damage during disasters highlights the critical importance of fostering community-based networks and institutions as a proactive strategy for disaster prevention and risk reduction.

The structure of this paper is as follows. Section 2 explains the conceptual framework adopted in this study and reviews how social capital has been defined and measured in existing studies. Section 3 introduces the context of Japan, which serves as our case, and outlines VDPOs used as indicators of social capital. Section 4 explains our dataset and presents descriptive statistics. Section 5 describes our empirical specification and presents regression results. Section 6 concludes.

2. Conceptual Framework

2.1. The United Nations Development Program (UNDP) model

This paper conducts an empirical analysis based on the framework proposed by UNDP (2004) [10]. In this framework, disaster risk is a function of physical exposure to hazard and vulnerability, based on the concept that the risk is not solely caused by natural events but strongly affected by human activities. In particular, vulnerability refers to multiple factors, including economic and social factors, that affect a person's or society's capacity to cope with and adapt to hazardous events. The framework is formulated as follows.

$$[\text{Risk}] = [\text{Hazard}] \times [\text{Vulnerability}]$$

Risk represents the damage caused by natural disasters, Hazard indicates the magnitude of natural hazards, and Vulnerability captures the capacity to address natural hazards. While vulnerability encompasses various dimensions, our study focuses especially on social capital as a key factor that affects the level of Vulnerability. Social capital plays a vital role in strengthening resilience and enabling more effective local disaster responses. Communities with strong social ties and networks are better able to prepare for, respond to, and recover from hazard events. Conversely, the erosion of social capital can exacerbate vulnerability and disaster impacts, especially among marginalized groups.

In our empirical analysis, we measure realized disaster risk using the number of fatalities and casualties resulting from natural disasters. To capture the hazard component of disaster risk, we rely on two types of data. First, we use records of evacuation advisories issued by local municipalities for hydrometeorological hazards. These advisories are based on forecasts of rainfall, wind speed, and likelihood of river flood, and thus serve as a composite indicator of flood and storm hazards. Second, we use data on seismic intensity for earthquakes to reflect the physical magnitude of earthquake events.

Our central hypothesis is that social capital mitigates vulnerability, reducing realized disaster risk given the level of hazards. To quantify social capital, we use novel data on the number of VDPOs established in each community, as well as the frequency of their annual activities. These variables serve as proxies for the strength and functionality of local social capital related to disaster preparedness and response. We elaborate further on the construction and interpretation of these social capital indicators in the following subsection.

2.2. Social Capital

The concept of social capital has gained scholarly attention since Coleman (1988), and Putnam et al. (1993) expanded the theory. Social capital refers to social relationships such as networks, norms, and trust, which can make societies more efficient through cooperative actions [11,12]. Since then, the concept of social capital has evolved and been investigated in various fields, including disaster risk reduction. Earlier works that investigated the role of social capital during and post disasters were mostly qualitative. For example, some studies analyzed the impact of social capital on disaster preparedness [13,14], while others examined its role in disaster response [15,16]. However, much of the earlier literature focused on the post-disaster recovery and reconstruction phase [17–22].

Recently, the literature started to quantitatively examine the role of social capital during natural disasters. As social capital encompasses broad elements, however, the measurement of social capital varies across studies, typically constrained by data availability. For example, Aldrich & Sawada (2015) analyzed the case of the 2011 Great East Japan Earthquake and tsunami, using pre-disaster crime rates as a proxy for social capital. They found that communities with lower crime rates before the disaster experienced lower mortality rates [5]. Yamamura (2010) used the number of public baths, community centers, and local firefighting teams as indicators of social capital. This study found that social capital mitigated the damage caused by various natural disasters [9]. Aldrich (2011) examined the 1995 Hanshin-Awaji Earthquake and used the number of newly established NGOs after the disaster as a measure of social capital. This study demonstrated that the presence of these organizations had a significant impact on post-disaster population recovery rates [3]. These are the studies that used administrative data and found positive effect of social capital on disaster preparedness and recovery.

An increasing number of studies used household survey to quantify social capital in more flexible manners. Abunyewah et al. (2023), for instance, conducted household survey in urban Ghana and constructed an index of social capital based on a number of questions on social networks, memberships, and trust. The study found the strong association between the social capital and disaster preparedness as well as community resilience [23]. Similar patterns were observed in rural China [24]. Some studies focus on a specific disaster by collecting data in the aftermath. Heller et al. (2005) found the positive association between the social networks and disaster preparedness in the 1994 Northridge Earthquake in the United States [25]. Tse et al. (2013) examined the 2008 Sichuan Earthquake and found that households with larger and denser social networks received more post-disaster assistance [26]. Akbar & Aldrich (2018) used the level of social trust as a measure of social capital and found strong positive association between social capital and life recovery after the 2010 flood in Pakistan [27]. Dinh et al. (2021) found the positive association between social capital measured by social network and membership in informal group and the speed of recovery after floods [28]. In general, the studies using survey data found that social capital facilitates disaster preparedness and recovery, but studies using primary data tend to focus on specific regions or particular disasters.

Lastly, an existing study closely related to ours is Shimada (2015), who analyzed VDPOs as an indicator of social capital, using prefectural-level data from 1981 to 2012. The study found that social capital had a positive effect on post-disaster recovery, measured by the change in population [8]. To conduct analysis at a finer level, we newly constructed the municipality-level data concerning VDPOs. Further, while this study used only the number of established VDPOs, we constructed data on their actual activities, particularly disaster drills in the normal time. Hence, our study examines the extent to which social capital, objectively defined across Japan, can mitigate natural disaster risk.

3. Setting

Japan is characterized by its geographical features, with approximately 70% of its landmass consisting of mountainous and hilly areas. Compared to the world's major rivers, Japan's rivers are relatively short in distance from their source to the mouth, and their steep gradients make the country highly susceptible to floods and landslides caused by heavy rainfall.

Furthermore, Japan is one of the most volcanically active countries in the world. Approximately one-fifth of all earthquakes with a magnitude of 6.0 or greater occur in Japan [29]. According to the World Risk Index 2024, Japan ranks third globally, after China and Mexico, in terms of high exposure to risks such as earthquakes and floods. However, despite these geographic vulnerabilities, the actual risk of damage from natural disasters in Japan remains relatively low by global standards [30]. This is largely attributed to Japan's sustained efforts to reduce societal vulnerability through various mitigation and preparedness measures.

In this disaster-prone country, VDPOs were first introduced in the early 1970s as part of urban earthquake preparedness. VDPOs are called *Jishu-bosai-soshiki* in Japanese, literally meaning "autonomous organization for disaster reduction" [31]. They are community-based groups formed by local residents who voluntarily engage in disaster prevention and mitigation activities, motivated by a shared sense of responsibility to protect their own community [32]. Over time, social connections among local residents for disaster prevention and response have declined due to improvements in physical infrastructure and public disaster response systems, as well as demographic shifts, including an aging population and changes in household composition. However, their importance was re-emphasized after the devastating 1995 Hanshin-Awaji Earthquake. The coverage rate, defined as the percentage of households within the operational areas of VDPOs, modestly increased from 37.1% in 1988 to 43.8% in 1995 [31]. It further increased to 85.4% by 2024 (see Figure 1), and the number of VDPOs has reached 167,233 as of April 2024 [33].

Before we turn to the data and analysis, it is important to clarify the difference between VDPOs and local firefighting teams. Local firefighting teams are part of municipal fire departments and carry out professional disaster response activities, such as extinguishing fires and rescuing residents. In contrast, VDPOs are community-led voluntary initiatives, with over 80% established by neighborhood associations. Therefore, VDPOs reflect the actual conditions of local social connections and community engagement.

Community-based disaster preparedness and response efforts are not unique to Japan. These actions can be observed globally. For example, the Community Emergency Response Team (CERT) program in the United States, led by the Federal Emergency Management Agency (FEMA), provides disaster preparedness knowledge and skills training to local volunteers based on community needs [34]. The Community-Based Disaster Risk Management program in Indonesia, a country prone to earthquakes, contributes to increasing community capacity and reducing vulnerability through several activities. These include the creation of hazard and evacuation maps, the provision of disaster preparedness and first-aid training, and the construction of risk-mitigating infrastructure [35]. Another country prone to earthquakes, Chile, has the Red de Prevención Comunitaria (RPC), a collaborative alliance between citizens, municipalities, companies, and other social sectors that works to identify local disaster risks and create a local prevention plan [36].

As disaster preparedness and risk reduction organizations become increasingly institutionalized worldwide, the findings of our study offer insights that extend beyond the Japanese context. By examining how VDPOs contribute to mitigating disaster impacts, our analysis highlights the broader importance of strengthening social capital as a complement to physical capital.

4. Data

4.1. Data on Risk and Hazard

We first define the scope of natural disasters analyzed in this study. As the primary objective is to examine the relationship between social capital and damage caused by natural disasters, the focus is on natural hazards for which community-level disaster preparedness could plausibly reduce human casualties. Based on this consideration, the study focuses on floods, storms, and earthquakes, which frequently occur in Japan and often result in human damage. These hazards are also relevant for assessing the role of community ties in reducing damage through daily disaster drills, evacuation guidance, and other life-saving activities.

For our purpose, we chose all the disasters that occurred in fiscal years 2014 to 2023, i.e., April 2014 to March 2024, and had at least one casualty or fatality. The focus on these years is due to the availability of data on VDPOs, as described below. There were 57 floods/storms and 28 earthquakes in our analysis period, which are listed in Appendix Table 1. For each selected disaster, we constructed municipality-level data on hazards and risks based on information from the FDMA. In cases where the municipal-level data was unavailable from FDMA, we supplementarily collected information obtained from the Cabinet Office as well as each prefectural government to construct and complete both risk and hazard data as much as possible.

The risk is measured by the number of fatalities and causalities. Note that the data on causalities, particularly on minor injuries, were only available at the prefecture level for some cases. Since the municipality-level breakdown is not available for such cases, we treat all the municipalities in these prefectures as missing, and thus, the sample size is slightly smaller for casualties and minor injuries. Data for municipalities are standardized to reflect administrative boundaries as of January 1, 2023, based on the Basic Resident Registration Survey by the Ministry of Internal Affairs and Communications. For example, cases where a town transitioned into a city or where multiple municipalities merged into a single administrative unit were adjusted to match the 2023 municipal boundaries. In such cases, the original data was mapped to the updated municipality codes and names corresponding to the current administrative divisions.

Table 1 presents the distribution of hazard levels of natural disasters in our study. For floods and storms, we use evacuation information as a proxy of hazard levels, instead of relying solely on meteorological data such as precipitation or weather warnings. This approach reflects the fact that storm- and flood-related hazards are typically the result of multiple and overlapping weather events, such as heavy rainfall, strong winds, storm surges, flooding, river overflows, and landslides. Therefore, rather than tracking just one of these factors, evacuation information is considered a more accurate indicator of both the occurrence and intensity of hazards, as it is issued by municipal governments based on a comprehensive assessment of these phenomena and the specific conditions of each region.

Level 0 is defined as cases where no evacuation information was provided and the evacuation advisory for the elderly and vulnerable was issued. Evacuation information in Japan is often announced preemptively and conservatively to prevent damage escalation, and this level is frequently issued. To better reflect situations with genuinely elevated disaster risk, we mainly focus on Level 1 and above, which are defined as evacuation recommendations or stronger, as hazard events. Level 1 is defined as cases where an evacuation advisory was issued. We have 2,802 municipality and disaster-level pairs that experienced this level during our observation periods from 2014 to 2023 (see Panel A). Level 2 is defined as cases with an evacuation order, and we have 2,324 pairs. Level 3 is defined as those with an emergency, and we have 158 pairs that experienced this level.

It is important to note that during the analysis period from 2014 to 2023, the guidelines regarding evacuation information were revised two times to ensure that disaster-related information would be communicated more clearly and facilitate timely evacuation actions. In particular, Level 3 (emergency) was introduced in June 2019. Additionally, Level 1 (evacuation advisory) was abolished in May 2021 and merged into Level 2 (evacuation order). In the regression analysis below, we examined the hazard level in two ways. First, we used the level as a continuous variable. Second, as the relationship between hazard and risk is not necessarily linear, we created a dummy variable for Level 1 and another one for Levels 2 and 3. The latter is essentially free from the change in the guidelines regarding evacuation information.

For earthquakes, Level 0 is defined as intensity 4 or below since limited fatalities or fatalities are observed in these earthquakes. Since Japan is frequently hit by earthquakes, the data construction becomes too cumbersome if we include minor earthquakes. Level 1 is defined as municipalities that experienced the intensity of lower 5. We have 212 municipality and disaster pairs that experienced this level (see Panel B). Level 2 is defined as pairs experiencing the intensity of upper 5, and we have 187 pairs. Similarly, Levels 3 and 4 are defined as those experiencing the intensity of lower and upper 6, and we have 83 and 25 pairs, respectively. We have 5 pairs for Level 5 that experienced the intensity of 7. In the regression analysis, we used the level as a continuous variable, and we also constructed two dummy variables, one indicating Levels 1 and 2, and the other Levels 3 or above.

4.2. Data on Vulnerability

We consider social capital to constitute an important component of vulnerability in the UNDP's framework, and we use the data on VDPOs as a measure of social capital. Specifically, we use the number of VDPOs and the number of regular disaster preparedness drills, both measured per 1,000 households. To avoid potential reverse causality, for any disasters that occurred in a given fiscal year (i.e., from April to March of the following year), we use the number of VDPOs as of April 1. This ensures that the data reflects the organizational structure in place before any disasters that occur during the corresponding fiscal year. The data on the number of drills conducted are based on the preceding fiscal year (from April 1 of the previous year to March 31 of the corresponding year), thereby capturing past activities without being influenced by subsequent disaster events.

In addition, household data used to convert these numbers into per capita terms are taken from the Basic Resident Registration Survey as of January 1 of each fiscal year. This timing is chosen to account for seasonal population movements in Japan, particularly those associated with school admissions and employment transitions that commonly occur in late March and early April. For instance, for the fiscal year 2014 (running from April 1, 2014, to March 31, 2015), the household data used to calculate the number of VDPOs is based on the population as of January 1, 2015, while the data used to standardize the number of preparedness drills corresponds to January 1, 2014, reflecting the temporal alignment described above.

4.3. Descriptive Statistics

Table 2 presents the descriptive statistics of damages. Since our observation is municipality and disaster pairs, we have many zeros, and thus, the means are small. Panel A shows that 261 municipality and disaster pairs experienced at least one fatality in floods or storms. Among these pairs, the mean is 3.24, and the maximum is 77. For the severe casualties, we have 349 pairs, with a mean of 1.70 and a maximum of 46. These numbers indicate that we have 846 fatalities and 593 serious causalities from floods and storms during the ten years of our observation period. For the injuries including minor ones, we have 1120 pairs, with a mean of 2.87 and a maximum of 178. Although we have data on missing persons, the cases are limited, and we did not include them in the regression analysis.

Panel B shows the descriptive statistics for earthquake damages. A total of 52 municipalities and disaster pairs recorded at least one fatality, among which the mean is 16.42, and the maximum is 189. Regarding the severe casualties, there are 116 pairs with a mean of 15.29 and a maximum of 772. These numbers correspond to a total of 854 fatalities and 1774 serious causalities caused by earthquakes over our observation period. For the injuries, including minor ones, we observed 280 municipality-disaster pairs, with a mean of 19.3 and a maximum of 1715. Since there was only one reported missing person’s data, this category was excluded from our regression analysis. The descriptive statistics show that natural disasters in Japan caused substantial human damage.

Panel C presents descriptive statistics on our social capital indicators. We have two variables at the municipality and fiscal year level; one is the number of VDPOs (per 1,000 households) at the beginning of the fiscal year, and the other is the number of disaster drills (per 1,000 households) conducted in the previous fiscal year. The mean number of VDPOs per 1,000 households is 6.4, indicating that Japan has one VDPO for about every 160 households. The mean number of annual disaster drills is 2.5, substantially smaller than the number of VDPOs. Since disaster drills are the major activity of VDPOs, which are usually conducted once a year, less than half of VDPOs are active. Since we used the previous year's value for the disaster drills, the sample size was reduced by one year.

Figure 2 illustrates the relationship between the hazard level, damages, and the number of VDPOs. Panel A shows some fatalities and casualties in Level 1 of floods and storms. The damages increased in Level 2, including extremely large numbers. Level 3 also records damages, but not with extreme numbers, probably due to the smaller number of pairs experienced Level 3. Panel B shows that while the damages in earthquakes are limited in Levels 1 and 2 (i.e., the intensity of lower and upper 5), they increase with Levels. Although we only have 5 observations, the damage in Level 5 is massive. In both Panels, the lines indicating municipalities with the above-median number of VDPOs are located below. This suggests that municipalities with better social capital are better able to mitigate damages given the hazard level they experience. Note that this figure does not necessarily correspond to our regression analysis since we include municipality fixed effect in our model to examine within-municipality variation in the number of VDPOs. Figure 2 presents patterns by simply splitting the sample municipalities with the median of VDPOs for illustration purposes.

5. Results

5.1. Regression Specification

We estimated the following regression model:

$$Damage_{i,j,k,t}=\beta_1 Hazard_{i,j}+\beta_2 SocialCapital_{j,t}+\beta_3 Hazard_{i,j}*SocialCapital_{j,t}+u_{i(,k)}+u_j+\varepsilon_{i,j,t}$$

Here, i denotes the disaster, j municipality in prefecture k, and t is the fiscal year. $Hazard_{i,j}$ is the level of hazard experienced in disaster i in municipality j. $SocialCapital_{j,t}$ indicates the number of VDPOs or the number of disaster drills conducted in the previous fiscal year in municipality j in fiscal year t. $SocialCapital_{j,t}$ is demeaned by the average of each fiscal year so that we can interpret β_1 as an average effect of hazard on damage. Our main parameter of interest is β_3, which captures the differential relationship between hazard and damages by the level of social capital. We hypothesize this term to be negative, suggesting that social capital prevents hazard from translating into damage. The terms u_i and u_j represent fixed effects for disasters and municipalities, respectively. Since at least one disaster occurred in each fiscal year, disaster fixed effects effectively absorb fiscal year fixed effects.

First, we estimate the model using standard errors clustered at the municipality level (j), to account for autocorrelation within municipalities. The second model includes disaster-by-prefecture fixed effect, $u_{i(,k)}$, allowing us to control for any prefecture-specific responses to each disaster. This model exploits variation across municipalities within the same prefecture for a given disaster. In the second model, we use standard robust standard errors as the clustering becomes too restrictive.

We add various fixed effects in our regression specification to interpret the estimated β_3 as the causal mitigating effect of VDPOs. However, potential endogeneity remains a concern. In particular, municipalities that have experienced disasters may respond by increasing their risk perception, leading to the establishment of new VDPOs or the intensification of activities by existing ones. These municipalities may also simultaneously implement other disaster prevention measures, which could reduce damages in future disasters. If so, the estimated β_3 would overestimate the impact of VDPOs. To address this concern, we conduct a subsample analysis excluding municipalities that experienced fatalities from any disaster in the past two years. Specifically, we exclude 3,077 municipality-disaster pairs (3.3%) for floods and storms and 1500 pairs (3.1%) for earthquake. Moreover, due to the lack of disaster records before 2014, we are unable to identify such municipalities for years 2014 and 2015. As a result, observations from 2014 and 2015 are also dropped from the subsample analysis. This restriction additionally serves as a robustness check, helping to rule out lingering influences from the catastrophic 2011 East Japan Earthquake, as we exclude data from the immediate aftermath.

5.2. Estimation Results

Table 3 reports the results for floods and storms, with Panel A using the full sample and Panel B focusing on a subsample that excludes municipalities with disaster-related fatalities in the preceding two years. Odd-numbered columns report estimates with clustered standard errors, while even-numbered columns include disaster-by-prefecture fixed effects. In each panel, the first sub-panel examines hazard as a continuous variable, whereas the second sub-panel employs hazard-level dummy variables to capture the observed non-linear relationships, as illustrated in Figure 2.

Columns 1 and 2 in Table 3 present results for the relationship between fatalities, hazards, and the social capital measured by the number of VDPOs. First, we find that the number of fatalities significantly increases with the hazard level, and the damages concentrate on hazard levels 2 and 3. The point estimate for β_3, i.e., the interaction between hazard and social capital measured by the number of VDPOs, is negative but insignificant. In columns 3 and 4, we used the number of disaster drills to indicate social capital but found an insignificant coefficient. These results indicate that social capital did not play a particular role in reducing fatalities in meteorological disasters. Qualitatively similar patterns are observed in the subsample analysis (Table 3, Panel B).

In columns 5 to 6, we present results for the relationship between severe casualties, hazards, and the number of VDPOs. We find a positive and non-linear relationship between the hazard and damages. Importantly, β_3, i.e, the interaction of hazard and the number of VDPOs, is negative and statistically significant. While one level increase in hazard causes 0.052 additional severe casualties, one more VDPOs per 1,000 households mitigates such increase by 0.0021 (Table 3, Panel A1). As the mean number of VDPOs per 1,000 households is 6.4, the increase of VDPOs from zero to the mean mitigates 0.013 severe casualties, which is about a quarter of additional damage caused by one level increase in hazard. Panel A2 shows that such a negative coefficient is particularly observed for hazard levels 2 and 3. These suggest that social capital helps communities prevent severe casualties in relatively severe flood and storm events. In columns 7 and 8, we have a similar magnitude of the coefficients for the interaction terms of the hazard and the number of disaster drills in Panel A1. Panel A2 shows a similar magnitude of negative coefficient for the interaction between severe hazard and disaster drills. However, these coefficients are statistically insignificant. Qualitatively similar patterns are observed in the subsample analysis reported in Panel B.

Columns 9 to 12 show the results for injuries, including minor ones, presenting even clearer patterns between damage, hazard, and social capital. The coefficient of hazard is all positive and significant, and the interaction is all negative and significant even for the number of disaster drills in Panel A1. Panel A2 also shows the negative and significant coefficient for the interaction between the severe hazard and the number of disaster drills. These results indicate that the social capital, measured by the number of VDPOs as well as the number of community-level disaster drills, successfully mitigates the human damage caused by meteorological disasters.

Table 4 presents the results for earthquakes in the same manner as Table 3. Columns 1 to 4 show that the severity of earthquake increases fatalities non-linearly, where the damages are particularly concentrated on Levels 4 or 5 (i.e., the earthquake intensity of upper 6 or 7). The interaction term between the weaker hazard and the number of VDPOs is negative and marginally significant in column 2. This may suggest that while social capital did not play an important role in mitigative deaths in a massive earthquake, it plays some role in a less devastative one, where the death may have been caused not by the immediate shock but by subsequent evacuation. Note that the coefficient is insignificant in Column 1, and this result is only suggestive. Relatedly, we find the negative significant coefficient of the interaction between the weaker earthquake and the number of disaster drills in column 3 but not in column 4.

For the casualties, columns 5 to 12 present similar patterns. First, the level of hazard increases casualties non-linearly. Particularly, the point estimate for the severe earthquake in Panel A2 is large. The interaction between the hazard and social capital is overall negative and significant in some columns. Although suggestive, these patterns indicate that social capital may help reduce casualties in moderately devastating earthquakes.

6. Discussion

6.1. Mechanisms

While we find that VDPOs have a positive impact on reducing human damage, especially from storms and floods, our quantitative results do not necessarily provide a clear reason. To discuss possible mechanisms behind our findings, we refer to the results of the survey conducted by FDMA in 2016. In this survey, municipal governments and fire departments were asked to select VDPOs within their jurisdictions and distribute questionnaires to them. In total, 1,000 VDPOs were selected, and 633 provided valid responses [37]. While we need to be cautious about the representativeness of the survey, which was not based on random sampling, the sample size is large, and the response rate is relatively high. Based on their results, VDPOs were typically formed in areas with a high risk of water-related disasters. 45.2% of them operated in regions with a risk of flooding, followed by areas prone to landslides (40.1%). Our findings of stronger impacts from floods and storms may reflect such patterns of VDPO establishment.

One possible mechanism behind the positive impact is enhanced preparedness [38]. Indeed, our empirical findings show that the number of disaster drills also matters. The FDMA survey reports that drills include fire extinguishing exercises (73.5%), evacuation guidance drills (59.7%), information gathering and communication drills (58.5%), and rescue and first aid training (49.6%). In addition, the survey reports that more than half of the VDPOs had predetermined action plans for what to do upon the issuance of evacuation information. Such community-level planning and training can improve the predictability of actions during disasters.

Another possible mechanism is improved knowledge on the local environment, including the location of vulnerable populations who may require assistance for evacuation [39]. In addition, social networks enable people to access and understand local disaster risk information [40]. In the FDMA survey, when asked about what they considered to be the most important role of VDPOs, 61.3% identified the dissemination of disaster-related knowledge as the top priority. This was followed by identifying individuals who require assistance during evacuations (44.5%), collecting information on safety and damage (37.1%), guiding evacuations (28.1%), and identifying hazardous locations (24.6%). These results indicate that VDPOs have a crucial role as information hubs.

Lastly, VDPOs contribute to faster and more appropriate evacuation responses during emergencies. According to the FDMA survey, of the 49.3% of VDPOs that had experienced disasters, 53.8% were involved in gathering information about safety confirmation and damage, and 31.4% provided evacuation guidance and basic supplies such as food and water. This is consistent with Zhao et al. (2025), which suggested that moral responsibility, strengthened by social capital, can foster behavioral change, leading to a greater willingness to participate in community emergency actions in response to disasters [41].

6.2. Possible caveat of VDPOs

While we have mostly focused on the positive aspects of VDPOs, qualitative studies also report the negative aspects of VDPOs. Based on participant observation in a certain VDPO, Bajek et al. (2008) pointed out that the VDPOs, which, in many cases, were formed under the umbrella of neighborhood associations, often included these members by default. Therefore, participation in VDPOs may not be entirely voluntary, nor does it necessarily reflect a strong personal commitment to disaster preparedness [31]. This differs from the more conventional notion of volunteering, where individuals actively choose to engage in specific activities based on personal motivation. While this observation is based on a specific case, the FDMA survey reports that 23.6% of VDPOs identified a low number of participants in disaster prevention activities as one of their major challenges. One-third of such VDPOs particularly pointed out the limited involvement of young generations.

It is also worth noting that not all community members have equal influence within the network or benefit equally from social capital. Zhao et al. (2025) highlighted that socio-demographic characteristics, such as gender, age, ethnicity, and socioeconomic status, can shape how individuals benefit from social capital in the context of disaster preparedness and response [41]. Aldrich (2012) pointed out that social capital can exacerbate prejudice, further marginalizing certain populations [42]. According to the FDMA survey, there are significant disparities in age and gender among VDPO participants. In over 60% of VDPOs, females account for less than 25% of board members, with 22.2% having no female board members at all. In terms of age, 48.0% of representatives were in their 60s, and 36.8% were aged 70 or older. These suggest that old males dominate the leadership of VDPOs.

7. Conclusion

Natural hazards have historically posed substantial threats to human societies, and the accelerating pace of climate change is expected to further increase both the frequency and severity of hazards. Hence, understanding the factors that enhance disaster resilience has become increasingly important. Leveraging a newly constructed nationwide dataset from Japan, our analysis provides empirical evidence that social capital, measured by the presence and activity of community-based disaster prevention organizations, plays a significant role in mitigating the damage caused by natural hazards.

Specifically, we find that municipalities with higher levels of social capital experienced significantly fewer casualties from floods and storms and possibly also from less destructive earthquakes. While such effects are less pronounced for fatalities, the overall pattern suggests that community-level social networks and collective preparedness efforts contribute to reducing disaster-related harm. These findings underscore the value of fostering strong local social ties and participatory institutions as a complement to physical infrastructure in disaster risk reduction strategies. While our analysis is based on the case of Japan, similar organizations have been established in several other countries. Hence, our findings offer a generalizable conclusion, although further studies are needed for different contexts, particularly those in developing countries, where social capital may play a stronger role in complementing weak physical capital.

References

[1] H. Ritchie, P. Rosado, M. Roser, Natural Disasters, Our World in Data (2022). https://ourworldindata.org/natural-disasters (accessed April 17, 2025).

[2] D.P. Aldrich, M.A. Meyer, Social Capital and Community Resilience, American Behavioral Scientist 59 (2015) 254–269. https://doi.org/10.1177/0002764214550299.

[3] D.P. Aldrich, The power of people: social capital's role in recovery from the 1995 Kobe earthquake, Nat Hazards 56 (2011) 595–611. https://doi.org/10.1007/s11069-010-9577-7.

[4] D.P. Aldrich, Social, not physical, infrastructure: the critical role of civil society after the 1923 Tokyo earthquake, Disasters 36 (2012) 398–419. https://doi.org/10.1111/j.1467-7717.2011.01263.x.

[5] D.P. Aldrich, Y. Sawada, The physical and social determinants of mortality in the 3.11 tsunami, Soc Sci Med 124 (2015) 66–75. https://doi.org/10.1016/j.socscimed.2014.11.025.

[6] A.M. Sadri, S.V. Ukkusuri, H. Gladwin, The Role of Social Networks and Information Sources on Hurricane Evacuation Decision Making, Natural Hazards Review 18 (2017) 04017005. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000244.

[7] M. Shoji, A. Murata, Social Capital Encourages Disaster Evacuation: Evidence from a Cyclone in Bangladesh, The Journal of Development Studies 57 (2021) 790–806. https://doi.org/10.1080/00220388.2020.1806245.

[8] G. Shimada, The role of social capital after disasters: An empirical study of Japan based on Time-Series-Cross-Section (TSCS) data from 1981 to 2012, International Journal of Disaster Risk Reduction 14 (2015) 388–394. https://doi.org/10.1016/j.ijdrr.2015.09.004.

[9] E. Yamamura, Effects of Interactions among Social Capital, Income and Learning from Experiences of Natural Disasters: A Case Study from Japan, Regional Studies 44 (2010) 1019–1032. https://doi.org/10.1080/00343400903365144.

[10] UNDP, Reducing Disaster Risk, A Challenge for Development, United Nations Development Program (2004). https://www.undp.org/publications/reducing-disaster-risk-challenge-development (accessed April 7, 2025).

[11] J.S. Coleman, Social Capital in the Creation of Human Capital, American Journal of Sociology 94 (1988) S95–S120.

[12] R.D. Putnam, R. Leonardi, R.Y. Nonetti, Making Democracy Work: Civic Traditions in Modern Italy, Princeton University Press, 1993. https://doi.org/10.2307/j.ctt7s8r7.

[13] J. Mimaki, R. Shaw, Enhancement of disaster preparedness with social capital and community capacity: A perspective from a comparative case study of rural communities in Kochi, Japan, SUISUI Hydrological Research Letters 1 (2007) 5–10. https://doi.org/10.3178/suisui.1.5.

[14] B.L. Murphy, Locating social capital in resilient community-level emergency

management, Nat Hazards 41 (2007) 297–315. https://doi.org/10.1007/s11069-006-9037-6.
[15] M.B. LaLone, Neighbors Helping Neighbors: An Examination of the Social Capital Mobilization Process for Community Resilience to Environmental Disasters, Journal of Applied Social Science 6 (2012) 209–237. https://doi.org/10.1177/1936724412458483.
[16] T. Schilderman, Adapting traditional shelter for disaster mitigation and reconstruction: experiences with community-based approaches, Building Research & Information 32 (2004) 414–426. https://doi.org/10.1080/0961321042000250979.
[17] D. Aldrich, Fixing Recovery: Social Capital in Post-Crisis Resilience, Journal of Homeland Security (2010). https://docs.lib.purdue.edu/pspubs/3.
[18] E. Chamlee-Wright, V.H. Storr, Social Capital as Collective Narratives and Post-Disaster Community Recovery, The Sociological Review 59 (2011) 266–282. https://doi.org/10.1111/j.1467-954X.2011.02008.x.
[19] N.E. Ganapati, In Good Company: Why Social Capital Matters for Women during Disaster Recovery, Public Administration Review 72 (2012) 419–427. https://doi.org/10.1111/j.1540-6210.2011.02526.x.
[20] M.E.B. Garrison, D.D. Sasser, Families and Disasters: Making Meaning out of Adversity, in: K.E. Cherry (Ed.), Lifespan Perspectives on Natural Disasters: Coping with Katrina, Rita, and Other Storms, Springer US, New York, NY, 2009: pp. 113–130. https://doi.org/10.1007/978-1-4419-0393-8_6.
[21] R.L. Hawkins, K. Maurer, Bonding, Bridging and Linking: How Social Capital Operated in New Orleans following Hurricane Katrina, British Journal of Social Work 40 (2010) 1777–1793. https://doi.org/10.1093/bjsw/bcp087.
[22] Y. Nakagawa, R. Shaw, Social Capital: A Missing Link to Disaster Recovery, International Journal of Mass Emergencies & Disasters 22 (2004) 5–34. https://doi.org/10.1177/028072700402200101.
[23] M. Abunyewah, M.O. Erdiaw-Kwasie, S.A. Okyere, G. Thayaparan, M. Byrne, J. Lassa, K.K. Zander, Md.N. Fatemi, K. Maund, Influence of personal and collective social capital on flood preparedness and community resilience: Evidence from Old Fadama, Ghana, International Journal of Disaster Risk Reduction 94 (2023) 103790. https://doi.org/10.1016/j.ijdrr.2023.103790.
[24] A. Xiong, Y. Li, The role of social capital in building community disaster resilience – empirical evidences from rural China, International Journal of Disaster Risk Reduction 110 (2024) 104623. https://doi.org/10.1016/j.ijdrr.2024.104623.
[25] K. Heller, D.B. Alexander, M. Gatz, B.G. Knight, T. Rose, Social and Personal Factors as Predictors of Earthquake Preparation: The Role of Support Provision, Network Discussion, Negative Affect, Age, and Education, Journal of Applied Social Psychology 35 (2005) 399–422. https://doi.org/10.1111/j.1559-1816.2005.tb02127.x.

[26] C.W. Tse, J. Wei, Y. Wang, Social Capital and Disaster Recovery: Evidence from Sichuan Earthquake in 2008 - Working Paper 344, Center for Global Development Working Paper (2013). https://www.cgdev.org/publication/social-capital-and-disaster-recovery-evidence-sichuan-earthquake-2008-working-paper-344 (accessed April 7, 2025).
[27] M.S. Akbar, D.P. Aldrich, Social capital's role in recovery: evidence from communities affected by the 2010 Pakistan floods, Disasters 42 (2018) 475–497. https://doi.org/10.1111/disa.12259.
[28] N.C. Dinh, F. Ubukata, N.Q. Tan, V.H. Ha, How do social connections accelerate post-flood recovery? Insights from a survey of rural households in central Vietnam, International Journal of Disaster Risk Reduction 61 (2021) 102342. https://doi.org/10.1016/j.ijdrr.2021.102342.
[29] CAO, White Paper on Disaster Management, Cabinet Office, Japan (2014). https://www.bousai.go.jp/kaigirep/hakusho/h26/honbun/index.html (accessed April 7, 2025).
[30] Bündnis Entwicklung Hilft, Word Risk Report 2024, (2024). https://weltrisikobericht.de/worldriskreport/# (accessed April 7, 2025).
[31] R. Bajek, Y. Matsuda, N. Okada, Japan's Jishu-bosai-soshiki community activities: analysis of its role in participatory community disaster risk management, Nat Hazards 44 (2008) 281–292. https://doi.org/10.1007/s11069-007-9107-4.
[32] FDMA, About US: Mission4 Enhance, Fire and Disaster Management Agency, Government of Japan (FDMA) (n.d.). https://www.fdma.go.jp/en/ (accessed June 7, 2025).
[33] FDMA, White Papers on Fire Service, Fire and Disaster Management Agency (2024). https://www.fdma.go.jp/publication/hakusho/r6/68138.html (accessed April 7, 2025).
[34] FEMA, Community Emergency Response Team (CERT), Federal Emergency Management Agency (2025). https://www.fema.gov/emergency-managers/individuals-communities/preparedness-activities-webinars/community-emergency-response-team (accessed April 7, 2025).
[35] IOM, Community-based disaster risk management: Experiences from Indonesia, International Organization for Migration (IOM) Indonesia (2011). https://www.humanitarianlibrary.org/sites/default/files/2013/07/30_CBDRM_Handbook_english_lo.pdf (accessed June 1, 2025).
[36] RPC, Red – Prevención de Incendios, Red de Prevención Comunitaria (RPC) (n.d.). https://reddeprevencioncomunitaria.cl/ (accessed June 2, 2025).
[37] FDMA, 1-1 Survey Results, the 3rd Meeting of the Study Group on Strengthening Voluntary Disaster Prevention Organizations, Fire and Disaster Management Agency, Government of Japan (FDMA) (2017).

https://www.fdma.go.jp/singi_kento/kento/kento189.html.
[38] A. Brunie, Household Awareness of What to Do in a Disaster: A Social Capital Approach, International Journal of Mass Emergencies & Disasters 28 (2010) 59–86. https://doi.org/10.1177/028072701002800103.
[39] R. Shaw, M. Ishiwatari, M. Arnold, Community-based disaster risk management, World Bank, 2011. https://documents.worldbank.org/en/publication/documents-reports/documentdetail/en/244761468261533701 (accessed June 2, 2025).
[40] S. Hanson-Easey, D. Every, A. Hansen, P. Bi, Risk communication for new and emerging communities: The contingent role of social capital, International Journal of Disaster Risk Reduction 28 (2018) 620–628. https://doi.org/10.1016/j.ijdrr.2018.01.012.
[41] G. Zhao, X. Hui, F. Zhao, L. Feng, Y. Lu, Y. Zhang, How does social capital facilitate community disaster resilience? A systematic review, Front. Environ. Sci. 12 (2025) 1496813. https://doi.org/10.3389/fenvs.2024.1496813.
[42] D.P. Aldrich, Building Resilience: Social Capital in Post-Disaster Recovery, University of Chicago Press, 2012. https://doi.org/10.7208/chicago/9780226012896.001.0001.

Table 1: Description of Hazard

Level	(1) Definition	(2) N
Panel A: Flood and storm		
Level 0	Lower-level or no evacuation information	93,928
Level 1	Evacuation recommendation	2,802
Level 2	Evacuation instruction	2,324
Level 3	Emergency safety measures, Disaster occurrence information	158
Panel B: Earthquake		
Level 0	Intensity of 4 or less	48,236
Level 1	Intensity of lower 5	212
Level 2	Intensity of upper 5	187
Level 3	Intensity of lower 6	83
Level 4	Intensity of upper 6	25
Level 5	Intensity of 7	5

Note: The observation unit is municipality and disaster pair.

Table 2: Descriptive statistics on damages and social capital

	(1) N	(2) mean	(3) SD	(4) min	(5) max
Panel A: Flood and storm					
# of fatalities	99,237	0.01	0.43	0	77
[non zero only]	261	3.24	7.66	1	77
# of missing persons	99,237	0.00	0.02	0	3
[non zero only]	24	1.21	0.51	1	3
# of severe injuries	98,649	0.01	0.22	0	46
[non zero only]	349	1.70	3.20	1	46
# of all injuries	97,921	0.03	0.94	0	178
[non zero only]	1120	2.87	8.30	1	178
Panel B: Earthquake					
# of fatalities	48,748	0.02	1.28	0	189
[non zero only]	52	16.42	36.03	1	189
# of missing persons	48,748	0.00	0.01	0	2
[non zero only]	1	2.00	.	2	2
# of severe injuries	48,666	0.04	3.72	0	772
[non zero only]	116	15.29	74.98	1	772
# of all injuries	48,586	0.11	8.64	0	1715
[non zero only]	280	19.3	112.4	1	1715
Panel C: Social capital					
# of VDPOs per 1,000 HH	17,410	6.4	7.8	0	77.3
# of disaster drills per 1,000 HH	15,087	2.5	5.1	0	88.4

Note: The observation unit is municipality and disaster pairs for Panels A and B, while it is municipality and year level for Panel C. There are several cases where only the prefecture-level data on the number of casualties are publicly reported, particularly for non-severe injuries. Since the municipality-level breakdown is not available for such cases, we treat all the municipalities in these prefectures as missing, and thus, the sample size is slightly smaller for casualties. # of VDPOs was measured at the beginning of each fiscal year, and # of disaster drills was for the previous fiscal year. Hence, the sample size for the latter is reduced by one year.

Table 3: Estimation results for flood and storm

Panel A: Full sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Outcome	Fatalities				Severe injuries				All injuries			
Panel A1: Categorical												
Hazard level	0.11***	0.084***	0.097***	0.067***	0.052***	0.038***	0.045***	0.028***	0.25***	0.18***	0.24***	0.16***
	(0.021)	(0.020)	(0.016)	(0.014)	(0.011)	(0.011)	(0.0061)	(0.0051)	(0.039)	(0.037)	(0.037)	(0.034)
Hazard level x # of VDPOs	-0.0021	-0.0011			-0.0021***	-0.0016***			-0.012***	-0.012***		
	(0.0027)	(0.0028)			(0.00071)	(0.00060)			(0.0028)	(0.0036)		
Hazard level x # of drills			0.0071	0.0087			-0.0010	-0.00024			-0.014***	-0.011**
			(0.0074)	(0.0078)			(0.0013)	(0.0012)			(0.0047)	(0.0048)
Panel A2: Dummies												
=1 if hazard level is 1	0.0088	-0.022	0.0038	-0.036**	0.032***	0.0089	0.032***	0.0060	0.24***	0.071	0.23***	0.049
	(0.0081)	(0.014)	(0.0097)	(0.017)	(0.0098)	(0.0072)	(0.012)	(0.0077)	(0.040)	(0.047)	(0.042)	(0.054)
=1 if hazard level is 2 or 3	0.27***	0.21***	0.24***	0.17***	0.12***	0.091***	0.098***	0.064***	0.54***	0.42***	0.51***	0.37***
	(0.056)	(0.053)	(0.042)	(0.036)	(0.029)	(0.029)	(0.016)	(0.014)	(0.11)	(0.10)	(0.10)	(0.093)
=1 if hazard level is 1	-0.000064	-0.00015			-0.00027	-0.00021			-0.012***	-0.011***		
* # of VDPOs	(0.00054)	(0.00078)			(0.00069)	(0.00071)			(0.0032)	(0.0033)		
=1 if hazard level is 2 or 3	-0.0047	-0.0020			-0.0053***	-0.0041***			-0.024***	-0.025***		
* # of VDPOs	(0.0076)	(0.0077)			(0.0019)	(0.0015)			(0.0071)	(0.0086)		
=1 if hazard level is 1			0.0018	0.0024*			0.0020	0.0019			-0.0074**	-0.0040
* # of drills			(0.0013)	(0.0015)			(0.0013)	(0.0012)			(0.0036)	(0.0038)
=1 if hazard level is 2 or 3			0.015	0.019			-0.0049	-0.0026			-0.037***	-0.030**
* # of drills			(0.020)	(0.021)			(0.0035)	(0.0029)			(0.014)	(0.014)
Municipality FE	X	X	X	X	X	X	X	X	X	X	X	X
Disaster FE	X	X	X	X	X	X	X	X	X	X	X	X
Clustered SE	X		X		X		X		X		X	
Disaster x prefecture FE		X		X		X		X		X		X
Number of observations	99237	99237	85573	85573	98649	98649	85084	85084	97921	97921	84392	84392

Panel B: Excluding municipalities that experienced death in the past 2 years (years 2014 and 2015 are also excluded)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Outcome	Fatalities				Severe injuries				All injuries			
Panel B1: Categorical												
Hazard level	0.096***	0.068***	0.094***	0.066***	0.042***	0.026***	0.042***	0.025***	0.21***	0.14***	0.21***	0.13***
	(0.018)	(0.015)	(0.017)	(0.014)	(0.0063)	(0.0054)	(0.0062)	(0.0053)	(0.034)	(0.027)	(0.034)	(0.026)
Hazard level x # of VDPOs	-0.0014	-0.00033			-0.0017**	-0.0012**			-0.010***	-0.011***		
	(0.0030)	(0.0031)			(0.00065)	(0.00054)			(0.0027)	(0.0036)		
Hazard level x # of drills			0.0088	0.010			-0.00071	-0.0000048			-0.013***	-0.0099**
			(0.0084)	(0.0085)			(0.0014)	(0.0013)			(0.0048)	(0.0050)
Panel B2: Dummies												
=1 if hazard level is 1	0.0059	-0.033*	0.0054	-0.034*	0.033**	0.0081	0.033**	0.0079	0.24***	0.073	0.23***	0.060
	(0.010)	(0.017)	(0.011)	(0.017)	(0.013)	(0.0084)	(0.014)	(0.0088)	(0.048)	(0.055)	(0.045)	(0.055)
=1 if hazard level is 2 or 3	0.23***	0.16***	0.23***	0.16***	0.090***	0.056***	0.089***	0.056***	0.42***	0.29***	0.43***	0.29***
	(0.045)	(0.038)	(0.044)	(0.037)	(0.017)	(0.014)	(0.016)	(0.014)	(0.090)	(0.074)	(0.090)	(0.074)
=1 if hazard level is 1	0.000052	0.000015			-0.000082	-0.000031			-0.011***	-0.010***		
* # of VDPOs	(0.00061)	(0.00091)			(0.00079)	(0.00082)			(0.0035)	(0.0035)		
=1 if hazard level is 2 or 3	-0.0024	0.00049			-0.0043**	-0.0030**			-0.020***	-0.021**		
* # of VDPOs	(0.0084)	(0.0087)			(0.0017)	(0.0013)			(0.0069)	(0.0088)		
=1 if hazard level is 1			0.0018	0.0025*			0.0018	0.0016			-0.0071*	-0.0033
* # of drills			(0.0013)	(0.0015)			(0.0014)	(0.0013)			(0.0038)	(0.0033)
=1 if hazard level is 2 or 3			0.021	0.024			-0.0040	-0.0018			-0.033**	-0.027*
* # of drills			(0.023)	(0.024)			(0.0038)	(0.0032)			(0.014)	(0.014)
Municipality FE	X	X	X	X	X	X	X	X	X	X	X	X
Disaster FE	X	X	X	X	X	X	X	X	X	X	X	X
Clustered SE	X		X		X		X		X		X	
Disaster x prefecture FE		X		X		X		X		X		X
Number of observations	80528	80528	77587	77587	80057	80057	77128	77128	79459	79459	76531	76531

Note: Estimated coefficients are reported. ***, **, and * indicate the 1%, 5%, and 10% levels of statistical significance, respectively. Numbers in parentheses are standard errors.

Table 4: Estimation results for earthquake

Panel A: Full sample

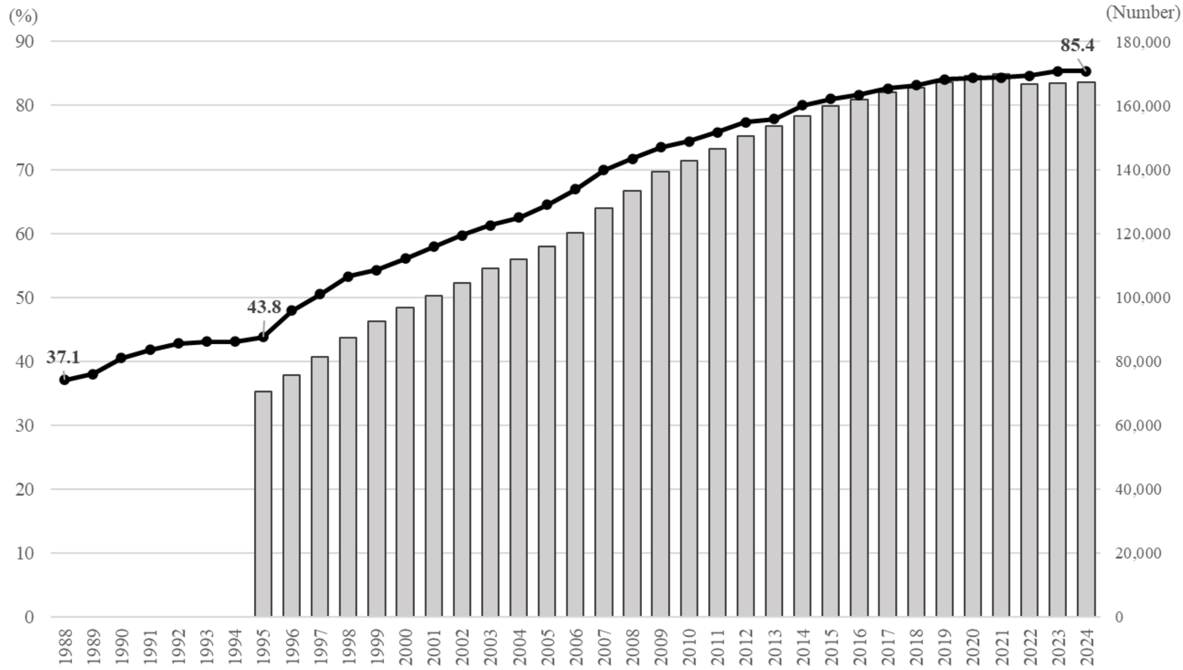
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Outcome	Fatalities				Casualties				Light injuries			
Panel A1: Categorical												
Hazard level	1.50***	1.46***	1.58***	1.51***	4.24**	3.59**	4.16**	3.54**	14.4**	13.8***	14.1**	13.7***
	(0.51)	(0.54)	(0.56)	(0.58)	(2.09)	(1.56)	(1.98)	(1.51)	(5.76)	(4.61)	(5.46)	(4.55)
Hazard level x # of VDPOs	0.080	0.071			-0.18	-0.22			-0.57	-0.61		
	(0.082)	(0.080)			(0.23)	(0.25)			(0.65)	(0.68)		
Hazard level x # of drills			0.031	0.027			-0.29	-0.27			-0.74	-0.63
			(0.073)	(0.067)			(0.31)	(0.28)			(0.78)	(0.69)
Panel A2: Dummies												
=1 if hazard level is 3 or less	0.18***	-0.35*	0.17***	-0.35*	0.49***	-0.72	0.49***	-0.83	3.44***	1.30	3.31***	0.89
	(0.056)	(0.20)	(0.057)	(0.20)	(0.11)	(0.65)	(0.11)	(0.74)	(1.03)	(1.82)	(1.00)	(2.09)
=1 if hazard level is 4 or 5	25.6***	24.3***	26.2***	24.8***	65.8*	59.8*	55.4**	48.9**	201.0**	191.3**	175.8**	164.1***
	(7.65)	(7.97)	(8.36)	(8.19)	(35.5)	(31.6)	(26.9)	(22.6)	(89.8)	(82.6)	(71.2)	(62.1)
=1 if hazard level is 3 or less	-0.0020	-0.032*			-0.0073	-0.074*			-0.15	-0.24*		
* # of VDPOs	(0.0059)	(0.019)			(0.0089)	(0.042)			(0.10)	(0.13)		
=1 if hazard level is 4 or 5	-0.12	-0.20			-6.77	-6.48			-19.2	-18.9		
* # of VDPOs	(1.77)	(1.72)			(6.59)	(6.17)			(18.7)	(17.9)		
=1 if hazard level is 3 or less			-0.024**	-0.044			-0.013	0.0024			-0.21**	-0.10
* # of drills			(0.011)	(0.027)			(0.020)	(0.059)			(0.099)	(0.14)
=1 if hazard level is 4 or 5			1.40	1.17			-3.38	-3.60			-5.68	-5.94
* # of drills			(1.88)	(1.70)			(4.55)	(4.43)			(10.7)	(10.4)
Municipality FE	X	X	X	X	X	X	X	X	X	X	X	X
Disaster FE	X	X	X	X	X	X	X	X	X	X	X	X
Clustered SE	X		X		X		X		X		X	
Disaster x prefecture FE		X		X		X		X		X		X
Number of observations	48748	48748	45275	45275	48666	48666	45196	45196	48586	48586	45119	45119

Panel B: Excluding municipalities that experienced death in the past 2 years (years 2014 and 2015 are also excluded)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Outcome	Fatalities				Casualties				Light injuries			
Panel B1: Categorical												
Hazard level	1.62***	1.53***	1.71***	1.62***	3.93**	3.29**	3.95**	3.34**	13.7***	12.9***	13.6***	13.1***
	(0.53)	(0.53)	(0.57)	(0.57)	(1.89)	(1.41)	(1.84)	(1.41)	(5.19)	(4.16)	(5.06)	(4.23)
Hazard level x # of VDPOs	0.051	0.037			-0.17	-0.21			-0.58	-0.64		
	(0.082)	(0.083)			(0.22)	(0.24)			(0.62)	(0.66)		
Hazard level x # of drills			0.042	0.032			-0.26	-0.24			-0.67	-0.56
			(0.072)	(0.065)			(0.29)	(0.27)			(0.73)	(0.65)
Panel B2: Dummies												
=1 if hazard level is 3 or less	0.18***	-0.27	0.17***	-0.27	0.44***	-0.94	0.45***	-0.96	3.44***	1.14	3.32***	0.94
	(0.066)	(0.19)	(0.067)	(0.19)	(0.15)	(0.83)	(0.15)	(0.86)	(1.23)	(2.31)	(1.16)	(2.46)
=1 if hazard level is 4 or 5	20.9***	19.5***	23.0***	21.8***	69.3*	63.0*	57.9**	51.0**	208.0**	198.5**	180.5**	168.7**
	(6.38)	(5.99)	(8.02)	(7.68)	(38.4)	(34.0)	(28.8)	(24.2)	(100.7)	(92.2)	(77.1)	(67.4)
=1 if hazard level is 3 or less	-0.0035	-0.030*			-0.0058	-0.074*			-0.16	-0.24*		
* # of VDPOs	(0.0064)	(0.017)			(0.011)	(0.042)			(0.11)	(0.13)		
=1 if hazard level is 4 or 5	0.92	0.89			-6.99	-6.72			-18.9	-18.6		
* # of VDPOs	(1.79)	(1.53)			(6.96)	(6.49)			(20.5)	(19.5)		
=1 if hazard level is 3 or less			-0.024*	-0.037			-0.0046	-0.00047			-0.20*	-0.12
* # of drills			(0.013)	(0.023)			(0.027)	(0.063)			(0.12)	(0.16)
=1 if hazard level is 4 or 5			1.15	0.99			-3.75	-3.93			-6.84	-6.99
* # of drills			(1.67)	(1.53)			(4.72)	(4.52)			(11.1)	(10.7)
Municipality FE	X	X	X	X	X	X	X	X	X	X	X	X
Disaster FE	X	X	X	X	X	X	X	X	X	X	X	X
Clustered SE	X		X		X		X		X		X	
Disaster x prefecture FE		X		X		X		X		X		X
Number of observations	42045	42045	40497	40497	41976	41976	40431	40431	41900	41900	40357	40357

Note: Estimated coefficients are reported. ***, **, and * indicate the 1%, 5%, and 10% levels of statistical significance, respectively. Numbers in parentheses are standard errors.

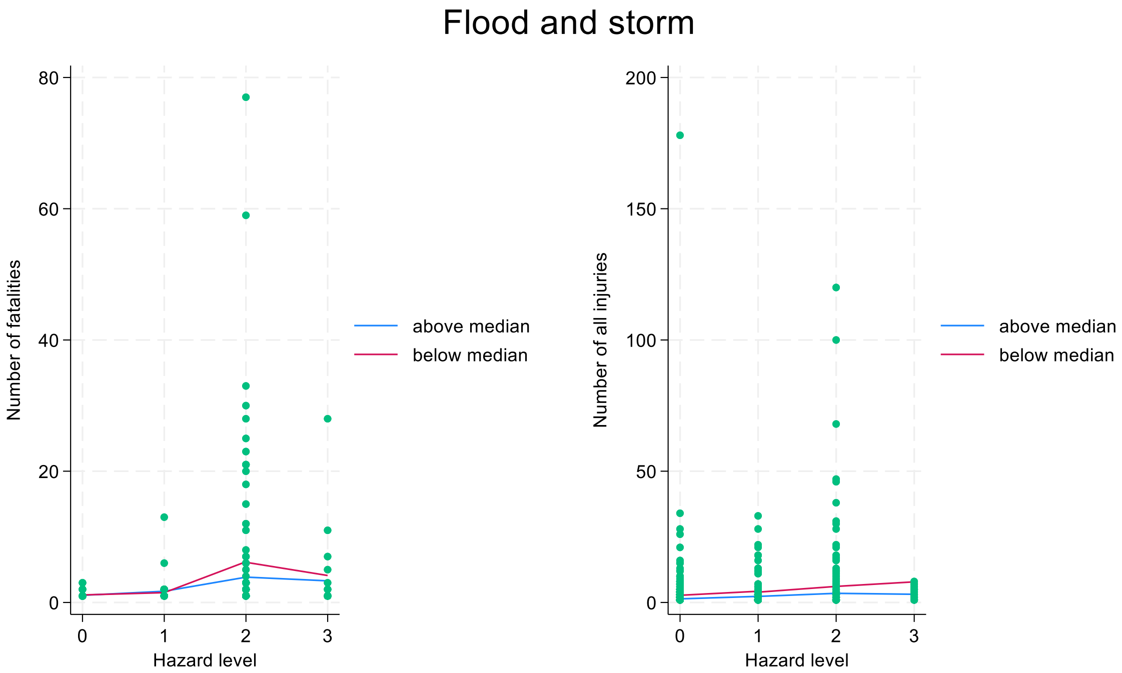
Figure 1: Number of VDPOs and The Coverage Rates



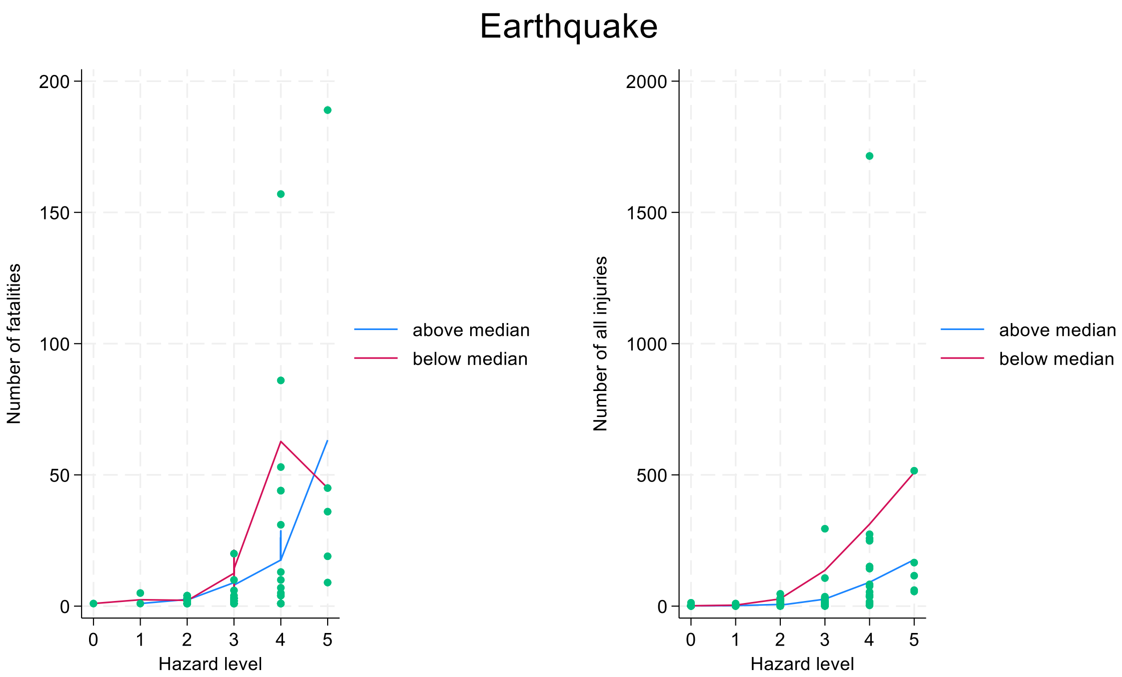
Note: The coverage rate refers to the percentage of households located in areas covered by the activities of VDPOs, relative to the total number of households. No data before 1987 are available. The data on coverage rate between 1988 and 1994 are based on Bajek et al. (2008), but they do not report the number of VDPOs during this period.
Source: Bajek et al. (2008), FDMA White Papers on Fire Service, various years.

Figure 2: Relationship between natural hazard and risk by the number of VDPOs

Panel A: Flood and storm



Panel B: Earthquake



Note: The figures plot only the municipality and disaster pairs that experienced any of each damage.

Appendix Table 1: The list of Natural Disasters in 2014-2023

Year	Date	Disaster
Panel A: Flood and storm		
2014	July 6	Typhoon No. 8 and Heavy rainfall since 6th July
2014	August 1	Typhoon No. 11 and 12
2014	August 15	Heavy rainfall since 15th August
2014	August 19	Heavy rainfall since 19th August
2014	September 29	Typhoon No. 18
2014	October 3	Typhoon No. 19
2015	July 4	Typhoon No. 11
2015	August 23	Typhoon No. 15
2015	September 9	Typhoon No. 18
2016	June 20	Heavy rainfall from 20th June
2016	August 20	Heavy rainfall from 20th August
2016	August 30	Typhoon No. 10
2016	September 6	Typhoon No. 13
2016	September 17	Typhoon No. 16
2017	June 30	Heavy rainfall since 30th June and Typhoon No. 3
2017	August 4	Typhoon No. 5
2017	September 13	Typhoon No. 18
2017	October 23	Typhoon No. 21
2017	October 28	Typhoon No. 22
2018	June 28	Torrential rain in July and Typhoon No. 12
2018	August 9	Typhoon No. 13
2018	August 23	Typhoon No. 20
2018	September 4	Typhoon No. 21
2018	September 28	Typhoon No. 24
2018	October 5	Typhoon No. 25
2019	June 29	Heavy rainfall since 29th June
2019	July 19	Typhoon No. 5
2019	August 6	Typhoon No. 8
2019	August 8	Typhoon No. 9
2019	August 14	Typhoon No. 10
2019	August 27	Heavy rainfall since 27th August
2019	September 9	Boso Peninsula typhoon
2019	September 21	Typhoon No. 17
2019	October 12	Typhoon No. 19
2020	June 29	Heavy rainfall since 29th June
2020	July 4	Torrential rainfall in July
2020	August 7	Heavy rainfall and low pressure since 6th August
2020	August 31	Typhoon No. 9
2020	September 3	Typhoon No. 10
2020	October 9	Typhoon No. 14
2021	July 1	Heavy rainfall since 1st July
2021	July 28	Typhoon No. 8
2021	August 10	Typhoon No. 9 and 10
2021	August 11	Heavy rainfall since 11th August
2021	September 10	Typhoon No. 14

2021	September 28	Typhoon No. 16
2022	July 14	Heavy rainfall since 14th July
2022	August 3	Heavy rainfall since 3rd August and Typhoon No. 8
2022	August 31	Typhoon No. 11
2022	September 17	Typhoon No. 14
2022	September 23	Typhoon No. 15
2023	June 2	Typhoon No. 2
2023	June 29	Heavy rainfall since 29th June
2023	July 15	Heavy rainfall since 15th July
2023	August 6	Typhoon No. 6
2023	August 10	Typhoon No. 7
2023	September 8	Typhoon No. 13
Panel B: Earthquake		
2014	November 22	Earthquake with epicenter in northern Nagano Prefecture
2015	May 30	Earthquake with epicenter off the west coast of the Ogasawara Islands
2015	July 13	Earthquake with epicenter in southern Oita Prefecture
2016	April 14	Earthquake with epicenter in Kumamoto Prefecture
2016	June 16	Earthquake with epicenter in Uchiura Bay
2016	October 21	Earthquake with epicenter in central Tottori Prefecture
2016	December 28	Earthquake with epicenter in northern Ibaraki Prefecture
2017	June 25	Earthquake with epicenter in southern Nagano Prefecture
2017	July 11	Earthquake with epicenter in Kagoshima Bay
2018	April 9	Earthquake with epicenter in western Shimane Prefecture
2018	June 18	Earthquake with epicenter in northern Osaka Prefecture
2018	September 6	Earthquake in Hokkaido
2019	January 3	Earthquake with epicenter in Kumamoto Prefecture
2019	February 21	Earthquake in Hokkaido
2019	June 18	Earthquake with epicenter off the coast of Yamagata Prefecture
2020	March 13	Earthquake with epicenter in Noto region, Ishikawa Prefecture
2021	February 14	Earthquake with epicenter off Fukushima Prefecture
2021	March 20	Earthquake with epicenter off Miyagi Prefecture
2021	May 1	Earthquake with epicenter off Miyagi Prefecture
2021	October 6	Earthquake with epicenter off Iwate Prefecture
2021	October 7	Earthquake with epicenter in north-west Chiba Prefecture
2022	January 22	Earthquake with epicenter in the Hyuga Sea
2022	March 16	Earthquake with epicenter off Fukushima Prefecture
2022	June 19	Earthquake with epicenter in Noto region, Ishikawa Prefecture
2023	May 5	Earthquake with epicenter off the Noto Peninsula
2023	May 11	Earthquake with epicenter in southern Chiba Prefecture
2024	January 1	Earthquake with epicenter off the Noto Peninsula
2024	March 15	Earthquake off the coast of Fukushima Prefecture

Note: There were 85 Natural disasters in 2014-2023, including 28 earthquakes (EQ) and 57 floods and storms (FS).