



# How natural hazards impact the social environment for vulnerable groups: an empirical investigation in Japan

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Received: 2 March 2020 / Accepted: 2 September 2020 / Published online: 16 September 2020  
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## Abstract

Much research has demonstrated that vulnerable people fare more poorly than non-vulnerable ones in disasters and crises across a variety of outcomes—including mental and physical health, disaster aid received, re-housing processes, and overall satisfaction with recovery. But little is known about how natural hazards change the social and political environment for those vulnerable groups. Some have argued that shocks raise the consciousness of civil society and decision makers so that conditions improve for vulnerable groups, while others believe that disasters have little or even negative impact on their status in society. This paper uses a new panel dataset across 17 years (1999 through 2015) of Japan's 47 prefectures to investigate how disasters impact discrimination rates for vulnerable groups, including women, the elderly, foreigners, and those with disabilities. Controlling for demographic and social factors, we find that disasters actually reduce discrimination against certain vulnerable groups—especially women and the elderly—while having no measurable impact on discrimination against other groups—foreigners and the disabled. These results bring with them important policy recommendations for local residents, disaster managers, and decision makers.

**Keywords** Discrimination · Japan · Natural hazards · Social environment · Vulnerable groups

## 1 Introduction

Natural hazards, including extreme weather events, flooding, and hurricanes, continue to take human lives and create high economic costs for societies around the world. Recent events have underscored the challenges created through the interaction of human habitation

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and such threats. Extreme weather events displaced seven million people between January and July of 2019, a new record (*New York Times* 12 September 2019). Beyond natural hazards, man-made shocks have also generated large numbers of internally displaced people (IDPs). The nuclear power plant meltdowns at the Fukushima Daiichi complex in March 2011, for example, forced more than 140,000 people from their homes and communities, with many still unable to return (Aldrich 2019).

During crises and shocks of all kinds, vulnerable groups continue to suffer disparate levels of death, injury, and dislocation. Vulnerability revolves around the conditions which make individuals and communities more susceptible to negative outcomes during crisis and disaster. More specifically, it refers to the “characteristics of a person or group in terms of their capacity to anticipate, cope with, resist and recover from a hazard” (Wisner et al. 2004). These challenges include those that society creates or amplifies for certain demographic groups along with disabilities, physical conditions, and illnesses that may make evacuation or survival less likely. Social vulnerability arises from prejudice and discrimination against people because of their gender, ethnicity, religion, class, caste, and disability status, while economic vulnerability can derive from qualities in the built environment such as unsafe conditions.

Gender and poverty continue to strongly correlate with negative disaster outcomes, including higher levels of morbidity and poorer mental health (Nahar et al. 2014). Women, young children, and the elderly, for example, saw higher death rates during the 2004 Indian Ocean tsunami (Aldrich 2012). During the 20-meter tsunami in Japan’s 3/11 triple disasters, death rates were highest among those over 65 years of age (Aldrich 2019; Ye and Aldrich 2019). Girls and women are more likely to be violated or sexually and physically abused by men during shocks and crises (Enarson et al. 2007). Even before disasters and crises arrive, disabled people are more likely to be excluded from the disaster planning process and hence have their needs overlooked (Roth 2018).

Policy makers have recognized these challenges, but the impact of their interventions remains unclear. Since the United Nations Convention of the Rights of Persons with Disabilities was adopted in 2006, disaster managers, planners, and local governments have sought to protect vulnerable groups during extreme weather events and shocks. This ambitious vision has been reflected in the Millennium Development Goals and a variety of pledges to inclusivity such as the Sendai Framework which prioritizes “understanding disaster risk in all its dimensions of vulnerability, capacity, exposure of persons and assets, hazard characteristics, and the environment.” Despite a recognition of the challenges facing vulnerable populations across the USA, the Federal Emergency Management Agency (FEMA) has in fact recently reduced the number of Disability Integration Advisers who seek to assist vulnerable populations (Rohrich 2018). Embodying this policy failure, during the California Pacific Gas and Electric Company (PG&E) blackouts in October 2019, elderly and disabled residents sat in the dark for days in a three-story apartment without anyone checking in on them (Lee and Fernandex 2019).

We might imagine that outcomes for vulnerable groups after repeated shocks sit along a spectrum of outcomes. In societies that face more, severe disasters, it is possible that decision makers will become more attuned to the social and environmental conditions that influence their lives and health. Observers may hope that faced with chronic stressors and repeated shocks, decision makers and civil society will prioritize improving outcomes for the elderly, vulnerable, and other demographic groups. If residents and politicians alike see higher death tolls among the elderly and infirm, for example, it may both raise their consciousness about the precarity of the vulnerable during normal times and also push them toward political action to improve the power and social status of vulnerable groups. For

example, Japan's coastal town of Rikuzentakata, devastated by the 3/11 tsunami on Japan's northeastern coast, saw nearly 1600 residents killed in the disaster. Soon after the shock, city planners argued that they would create an intentionally inclusive community which would include foreigners, wheelchair users, LGBTQ community members, and the elderly without barriers (Author site visit 2018). Rikuzentakata has followed through by seeking to include a variety of vulnerable groups in recovery planning and in disaster drills.

At the same time, though, it is not difficult to imagine that different politicians and communities may not use disasters as moments of learning. They may seek to play the “blame game” after a shock, display low sensitivity to issues of vulnerability, and undertake escape from responsibility (see Boin et al. 2008). If this scenario is more common, it is unlikely that shocks and disasters will have any measurable impact on the conditions for vulnerable groups. If the disabled, elderly, and other groups have a harder time mobilizing politically, they may even find that their positions are worsened by shock, as majority members or interest groups holding political power may have priority for aid, assistance, and resources for rebuilding. Our paper seeks to illuminate—in one advanced, industrialized country—which of these patterns has been more visible over two decades.

This paper makes several contributions to the field. First, it is among the first to look not at how shocks directly impact vulnerable groups—a well-studied topic—but rather at how extreme weather events and natural hazards impact societal approaches to these groups. Social scientists have studied how certain groups are deemed as “worthy” through deliberate framing attempts by gate keeping organizations and politicians. Here, we seek to illuminate how shocks themselves may alter the perspective of those with political power along with civil society as a whole.

Next, rather than relying on a handful of cases or qualitative impressions, this paper uses a new, *sui generis* dataset with nearly 800 observations which cover a decade and a half of nation-wide events. By using a large-N approach at this scale, we can better capture patterns across space and time rather than rely on impressionistic observations or anecdotes. We supplement the regression analysis with observations from fieldwork in disaster-affected communities.

Finally, our article provides concrete recommendations to decision makers, disaster managers, Non-Governmental Organizations (NGOs), and vulnerable populations. We believe that this paper moves beyond the standard arguments about the policies necessary to assist vulnerable populations to better understand that there are differences across vulnerable groups and also differences over time.

## 1.1 Literature review

The literature on the impact of natural hazards and threats on the status of vulnerable groups is split. Some scholars have argued that disasters can serve as focusing events for decision makers (Birkland 1996), that is, moments when increased attention on a public issue may lead to a new approach to managing it. Observers argue that massive catastrophes, such as those that struck northeastern Japan in March 2011, provide a moment where decision makers can move away from standard operating procedures to take on new, creative approaches to major problems (Samuels 2013). For example, following the meltdowns at the Fukushima Daiichi nuclear power plants, the Japanese government in fact reverted to the status quo on nuclear power, but other nations around the globe, including Germany and Switzerland, altered their energy programs (Aldrich et al. 2018). More germane to our focus here on disasters, following the 2011 Christchurch earthquake in New Zealand

the government published an updated and revised set of planning, recovery, and response guidelines to better integrate the disabled community into disaster management (MCDEM 2013). In these cases, shocks helped decision makers alter long-standing institutions and develop ones to better handle actual conditions.

Earlier scholarly work concerning social behaviors during and after disasters focused on enhanced community connections, declines in crime and other antisocial behaviors, and the development of therapeutic communities (Fritz 1961; Barton 1969; Quarantelli and Dynes 1972). These studies argued that the communities become a kind of “paradise” (Solnit 2009) aftershocks because survivors in the communities were more likely to take positive attitudes and behaviors, such as altruism, toward others. Should this altruism include vulnerable groups, negative behavior such as discrimination against the elderly, women, and other groups may decrease.

At the same time, however, some scholars have seen crises and catastrophes as moments when preexisting institutional and personal biases against the vulnerable and disabled become more visible and even more intense. Even before a flood or hurricane, disabled and vulnerable population face access challenges, and the advent of a natural hazard makes their situation even more precarious. “Unfortunately, disasters tend to increase the level of discrimination against people with disabilities” (Alexander 2011, p. 388). This may be due to deliberate bias on the part of first responders, disaster managers, and decision makers or it may be because of a lack of knowledge and resources. For example, if elderly, disabled, and migrant worker populations have not been included in disaster planning, they may nonetheless be blamed should they need additional assistance during crises. Whatever the case, some believe that disasters do little to improve the conditions for the disadvantaged and vulnerable. We have already mentioned that the US government recently reduced resources available to vulnerable populations despite rising numbers of extreme weather events.

Our paper seeks to shed light on this debate through a new data set capturing discrimination against vulnerable groups over time in an advanced industrial democracy which faces a wide variety of natural hazards.

## 1.2 Data

We developed a 17-year time series, cross-sectional (TSCS) panel dataset on all of Japan’s 47 prefectures from 1999 to 2015, resulting in 799 prefecture-year observations. We selected this period for analyses based on the availability of consistent data. The Japanese Ministry of Justice (*Hōmushō*) collects discrimination data under the category of Human Right Violations (*Jinken shinpan tōke*), and Japan’s Fire Disaster Management Agency (*Shōbōchō*) collects information on disaster impact in its *White Paper on the Fire Service* (*Shōbōhakusho*). We list all sources for the dataset in Appendix 1.

## 1.3 Variables

### 1.3.1 Dependent variables

As mentioned above, because the elements such as gender, age, race/ethnicity, and disability can constitute social vulnerable groups in disasters, we begin with the assumption that behaviors and attitudes toward these groups vary. As a result, we employ four dependent variables—(1) discrimination against women, (2) discrimination against elderly people, (3) discrimination

against foreigners, and (4) discrimination against those with disabilities. Each dependent variable captures the number of recorded discrimination cases against each vulnerable group per 10,000 persons in each prefecture per year in order to control for the overall population, normalizing the discrimination cases against the broader population in the prefecture. We calculate this as per Eq. (1) below:

$$\text{Discrimination Against Vulnerable Groups}_{it} = \frac{\text{Vulnerable Group Discrimination Cases}_{it}}{\text{Vulnerable Group Population}_{it}} \quad (1)$$

In this case,  $i$  refers to the administrative boundary of the Japanese prefecture and  $t$  refers to the year. So, for example, measure of discrimination across those with disabilities is calculated using the sum of Japanese residents recognized as physically handicapped persons, mentally handicapped persons and cerebrally handicapped persons per year per prefecture.

### 1.3.2 Independent variables

**1.3.2.1 Disaster impact** As previous studies have done (Matsubayashi et al. 2013), this paper utilizes the proportion of households affected by natural hazards in prefectures each year as the disaster impact variable. It is calculated as follows:

$$\text{Disaster Impact}_{it} = \frac{\text{Disaster-affected Household Number}_{it}}{\text{Household Number}_{it}} \quad (2)$$

### 1.3.3 Control variables

In order to control the characteristics that may both affect dependent and independent variables, this study also includes variables to take into account factors that may influence levels of discrimination. For example, we include a variety of lagged disaster impact variables because the consequences of a shock or crises on new societal norms, attitudes, and policies may not be immediate.

Additionally, we have to take into account other conditions which might alter the ways that civil society and the state encounter and interact with vulnerable communities. These include population density, share of women, share of the elderly (defined here as individuals over 65), share of foreigners, share of the population with a disability (which sums up the population of physically handicapped persons, mentally handicapped persons and cerebrally handicapped persons), the employment rate, Gross Domestic Product (GDP) per capita, disaster recovery expenditure rate, and Nonprofit Organizations (NPOs) per capita. The descriptive statistics of the variables are shown in Table 1.

Note that we have no missing data for these observations and do not need to employ multiple imputation or other techniques to control for observations omitted at random or otherwise.

**Table 1** Descriptive statistics

Variables	N	Mean	SD	Min	Max
<i>Dependent variable</i>					
Discrimination against women	799	0.013	0.022	0.000	0.247
Discrimination against elderly people	799	0.030	0.050	0.000	0.420
Discrimination against foreigners	799	0.661	1.037	0.000	8.313
Discrimination against disabled people	799	0.418	0.372	0.000	2.475
<i>Independent variables</i>					
Disaster impact	799	0.001	0.007	0.000	0.180
Disaster impact ( $t - 1$ )	799	0.001	0.007	0.000	0.180
Disaster impact ( $t - 2$ )	799	0.001	0.007	0.000	0.180
Disaster impact ( $t - 3$ )	799	0.001	0.007	0.000	0.180
<i>Control variables</i>					
Population density (log)	799	1.197	0.982	-0.376	4.122
Women proportion	799	0.517	0.010	0.492	0.534
Elderly proportion	799	0.230	0.039	0.121	0.336
Foreigner proportion	799	0.012	0.007	0.002	0.034
Disability proportion	799	0.047	0.011	0.019	0.075
Employment rate	799	1.629	1.712	0.396	8.141
GDP per capita	799	3.696	0.772	2.523	8.325
Disaster recovery expenditure rate	799	0.008	0.014	0.000	0.190
NPO per capita	799	0.000	0.000	0.000	0.001

## 2 Methods

To explore the relationship between natural hazards and measurable discrimination against vulnerable groups, we utilized the prefecture-level's fixed-effect model to control for the time-invariant characteristics of prefectures (the Japanese equivalent of North American states). Generally, the pooled OLS regression of the panel data can be expressed as Eq. (3):

$$Y_{it} = \alpha + \beta X_{it} + v_i + \varepsilon_{it} \quad (3)$$

where dependent variable  $y$  for prefecture  $i$  at time  $t$  is represented as  $Y_{it}$ ,  $\alpha$  represents the constant of the regression. The main independent variable  $X$  for prefecture  $i$  at time  $t$  is represented as  $X_{it}$ , and  $\beta$  is the regression coefficient of the independent variable. The  $v_i$  represents the time-invariant characteristics of each prefecture, and  $\varepsilon_{it}$  is the error term of prefecture  $i$  at time  $t$ . In order to control the time-invariant characteristics  $v_i$ , the fixed-effect model subtracts Eq. (3) so that the time-averaged of the pooled regression is expressed as Eq. (4) below:

$$\bar{Y}_i = \alpha + \beta \bar{X}_i + v_i + \bar{\varepsilon}_i \quad (4)$$

where  $\bar{Y}_i$ ,  $\bar{X}_i$ , and  $\bar{\varepsilon}_i$  represent the time-average of dependent variables, independent variables, and the error term. The subtraction of Eq. (3) and Eq. (4) can be written as follows:

$$Y_{it} - \bar{Y}_i = \beta (X_{it} - \bar{X}_i) + (\varepsilon_{it} - \bar{\varepsilon}_i) \quad (5)$$

It can also be written as:  $\Delta Y_{it} = \Delta \beta X_{it} + \Delta \varepsilon_{it}$  (6).

The  $\Delta Y_{it}$ ,  $\Delta X_{it}$  and  $\Delta \varepsilon_{it}$  in Eq. (6) are the  $Y_{it} - \bar{Y}_i$ ,  $X_{it} - \bar{X}_i$  and  $\varepsilon_{it} - \bar{\varepsilon}_i$  in Eq. (5). In Eq. (6), the time-invariant characteristics of each prefecture are removed by subtracting the pooled OLS regression and time-averaged regression. This forms the basis of our fixed-effect model.

In this study, the application of fixed-effect models can be expressed as Eq. (6).

$$\Delta D_{it} = \Delta \beta_1 DI_{it} + \Delta \beta_2 DI_{it-1} + \Delta \beta_3 DI_{it-2} + \Delta \beta_4 DI_{it-3} + \Delta \beta_{CV} CV_{it} + \Delta \beta_5 T_i + \Delta \varepsilon_{it} \quad (6)$$

where  $D_{it}$  represents the discrimination against vulnerable groups,  $DI_{it}$  equals the disaster impact, and  $CV_{it}$  is the vector of controlling variables. Because natural hazards can have long-term consequences on the prefectures, we also include lagged value of  $DI$  in the estimation. In Eq. (6),  $DI_{it-n}$  represents the disaster impact at time  $t - n$  in prefecture  $i$ , and the  $n=1, 2, 3$ . The setting of maximum value of  $n$  rests on the work carried out by previous studies that utilized the same quantitative methods (Matsubayashi et al. 2013; Keerthiratne and Tol 2018; Yamamura 2015). In order to control the time trend of the years, the  $T_i$  is also included in the estimation.

### 3 Results

Before estimating the coefficients of the fixed-effect model, we visually inspect the time trends of the averaged dependent and independent variables in Fig. 1. The solid line is the time trend of disaster impact. The two periods of increased disaster impact in 2004 and

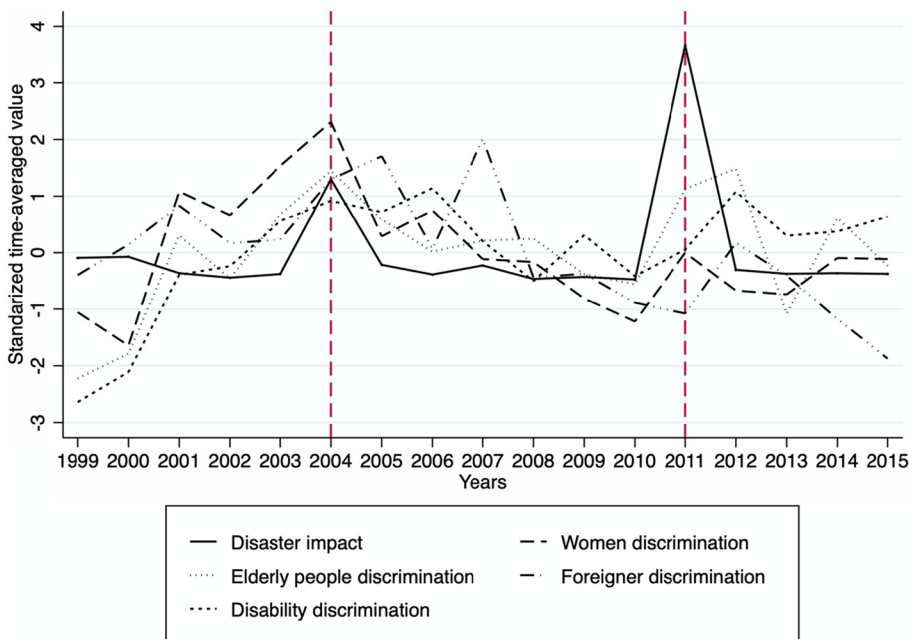


Fig. 1 Discrimination and disaster impact over time

2011 are marked by the two vertical red dash-lines indicating the 2004 Chūetsu Earthquakes and 2011 Great East Japan Earthquake. From this figure, because the lines of the discrimination toward vulnerable groups are all different from the line of disaster impact, we see little obvious time relationship between disaster impact and the discrimination against the vulnerable groups. However, we still include the time variable to statistically control the potential relationship of the time trend.

Then, we begin to estimate the relationship between disaster impact and discrimination against vulnerable groups separately utilizing the fixed-effect model. At first, we include only the disaster impact at time  $t$  in the estimation, with the results shown in Table 2.

**Table 2** Discrimination against vulnerable groups

Variables	Model (1)	Model (2)	Model (3)	Model (4)
	Women	Elderly	Foreigners	Disabilities
Disaster impact	0.00951 (0.0527)	-0.226** (0.111)	-3.301** (1.612)	-1.341* (0.738)
Population density (Log)	0.0270 (0.0292)	-0.0996 (0.0984)	4.558** (2.044)	-0.703 (0.510)
Women proportion	0.0746 (0.807)			
Elderly proportion		0.0176 (0.258)		
Foreigner proportion			-34.99 (32.31)	
Disability proportion				-13.53*** (4.394)
Employment rate	0.00225 (0.00176)	0.00329 (0.00367)	-0.0434 (0.0845)	0.0151 (0.0287)
GDP per capita	0.000519 (0.0133)	0.00671 (0.0197)	0.234 (0.283)	-0.0365 (0.0953)
Disaster recovery expenditure rate	-0.0243 (0.0456)	-0.230* (0.127)	9.328*** (2.571)	-0.824 (0.734)
NPO per capita	24.54* (13.76)	85.96** (33.38)	-505.5 (690.7)	404.8 (255.7)
Constant	-0.0749 (0.442)	0.0904 (0.145)	-5.375* (2.903)	1.633** (0.807)
Observations	799	799	799	799
$R^2$	0.072	0.064	0.060	0.091
Number of prefectures	47	47	47	47
Within $R^2$	0.0715	0.0643	0.0601	0.0913
Between $R^2$	0.0934	0.0571	0.138	0.000105
Overall $R^2$	0.00725	0.0228	0.0178	0.00182
Year effect	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

\*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$



Table 2 displays the results of shocks impact on recorded discrimination events against vulnerable groups. The results suggest that disaster impact has a negative and statistically significant correlation with discrimination against elderly people, foreigners and disabilities in that year. Interestingly, it has no statistically significant connection with reported discrimination against women. This indicates that disaster impact quickly correlates with drops in measurable discrimination levels against elderly people, foreigners and those with disabilities.

Now, we add in the lagged disaster impacts at time  $t-1$ , 2 and 3 into the estimation to explore the long-term effect of disaster impact, and the results are shown in Table 3.

Table 3 shows the results of disaster impact on recorded discrimination against vulnerable groups including one-, two- and three-year lags to explore the persistent effect of disaster on discrimination. For discrimination against women, consistent with the results in Table 1, the disaster impact does not have significant correlation with it for either the short term or long term.

In terms of discrimination against elderly people, the results show that in the first and second years after shocks, disaster impact has negative and significant connections with the discrimination against elderly people. This means that the disaster impact has a persistent decreasing correlation with the discrimination against elderly people.

Regarding discrimination against foreigners, even though the time gap is included, only the disaster impact at that year has a negative and significant correlation with the discrimination against foreigners. This means that the disaster impact does not have a measurable persistent connection with foreigners.

Finally, concerning the discrimination against those with disabilities, the result changes from those in Table 1. In our new results in Table 3, we found no significant significance in that year, while in the second and fourth year, we see positive and significant results. This means that disaster impact does not correlate with the discrimination against those with disabilities at that year, but it will do correlate with an increase in discrimination over the long-term.

We now begin to refine our models and take extreme outliers into account. As shown in Fig. 1, from 1999 to 2015, there were two large disasters, namely the 2004 Niigata earthquake and the 3/11 triple disasters. Table 4 shows the most affected year and prefectures of the disasters from 1999 to 2015.

From this table, we can see that Miyagi Prefecture was the most affected by the Great Eastern Japan Earthquake (GEJE) in 2011, while Niigata prefecture was most influenced by the 2004 Chūetsu Earthquake in 2004. The disaster affected 164,537 households in Miyagi Prefecture 2011, some 18% of the total. While during the Chuetsu Earthquake in Niigata, there were 25,018 households affected by disaster, they represented 3% of the total number of households in the prefecture. Comparing these two percentages, we can understand that the 3/11 triple disasters had a massive impact in Miyagi Prefecture. Past scholars have dropped influential outliers when their presence strongly influences regression estimates (Choi 2009). Given this disproportionate impact on the communities of Miyagi Prefecture, we rerun our analyses with it removed to ensure that the results are more representative of the standard disaster Japan experienced over the 17-year period of interest. The results are displayed in Table 5.

**Table 3** Discrimination against vulnerable groups (with time lag)

VARIABLES	Model (5)	Model (6)	Model (7)	Model (8)
	Women	Elderly	Foreigners	Disabilities
Disaster impact	0.00461 (0.0545)	−0.268* (0.137)	−3.340** (1.610)	−0.815 (0.832)
Disaster impact ( $t-1$ )	0.0713 (0.0978)	−0.305* (0.175)	−5.097 (4.394)	3.238** (1.402)
Disaster impact ( $t-2$ )	−0.0336 (0.0383)	−0.0791 (0.132)	4.323 (5.337)	0.953 (0.649)
Disaster impact ( $t-3$ )	−0.107 (0.0808)	−0.115 (0.113)	0.146 (3.936)	1.976* (1.060)
Population density (Log)	0.0285 (0.0288)	−0.0978 (0.0965)	4.541** (2.041)	−0.727 (0.521)
Women proportion	0.0357 (0.808)			
Elderly proportion		−0.0185 (0.258)		
Foreigner proportion			−35.10 (32.20)	
Disability proportion				−13.42*** (4.387)
Employment rate	0.00227 (0.00177)	0.00306 (0.00366)	−0.0443 (0.0843)	0.0179 (0.0287)
GDP per capita	0.000804 (0.0133)	0.00732 (0.0197)	0.232 (0.284)	−0.0444 (0.0959)
Disaster recovery expenditure rate	−0.0161 (0.0486)	−0.177 (0.119)	9.317*** (2.900)	−1.491* (0.795)
NPO per capita	23.70* (13.92)	78.97** (32.78)	−513.6 (694.0)	473.8* (253.2)
Constant	−0.0579 (0.443)	0.0936 (0.144)	−5.337* (2.905)	1.676** (0.817)
Observations	799	799	799	799
$R^2$	0.074	0.067	0.062	0.097
Number of prefectures	47	47	47	47
Within $R^2$	0.0736	0.0665	0.0624	0.0967
Between $R^2$	0.0948	0.0555	0.138	0.000167
Overall $R^2$	0.00775	0.0227	0.0177	0.00200
Year effect	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

\*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$

**Table 4** Ten observations with the largest proportion of disaster-affected households

Proportion of affected households	Number of affected households	Prefecture	Year	Major disasters
0.180	164,537	Miyagi	2011	Earthquake
0.031	25,018	Niigata	2004	Earthquake
0.026	28,954	Ibaraki	2011	Earthquake
0.024	9407	Kagawa	2004	Typhoon
0.020	15,163	Fukushima	2011	Earthquake
0.014	3551	Fukui	2004	Earthquake
0.013	2710	Tottori	2000	Earthquake
0.012	5796	Miyazaki	2005	Typhoon
0.011	4534	Wakayama	2011	Typhoon
0.010	6488	Kumamoto	1999	Typhoon

Compared with the results from Table 3, several changes are visible. First, in terms of discrimination against women, the coefficient of the disaster impact during the second year becomes significant and positive, while in the fourth year, it changes to significantly negative. These results mean that when excluding extreme disaster cases, disasters seem to promote discrimination against women for a relatively short term. However, over the long term, disasters help to reduce the discrimination against women.

Second, in terms of discrimination against elderly people, when excluding extreme outliers, the negative effect of disasters become stronger and longer. These results suggest that the huge natural hazards may weaken the negative influence of disasters on the discrimination against elderly people. Next, the negative correlation between disasters and discrimination against foreigners becomes non-significant. This suggests that the connection of disaster and discrimination against foreigners may only exist in huge disasters. Finally, the correlation between disaster and discrimination against those with disabilities becomes insignificant in both second and fourth year after the shock. This means only huge disasters have a positively short or medium-term effect on the discrimination against disabilities.

## 4 Conclusion and discussion

Using a new dataset focused on Japanese disasters and recorded discrimination against vulnerable groups, we have sought to illuminate a new facet of shocks. Rather than retreading well-travelled ground on the impact of disasters on the vulnerable, we have instead sought to show how shocks may correlate with changes in attitudes and behaviors toward vulnerable groups. Our dataset shows that at least the medium and long term, disasters and shocks

**Table 5** Analysis of discrimination against vulnerable groups (with time lag and without Miyagi Prefecture)

Variables	Model (9)	Model (10)	Model (11)	Model (12)
	Women	Elderly	Foreigners	Disabilities
Disaster impact	0.0958 (0.562)	-1.497*** (0.519)	-2.730 (12.53)	-4.637 (4.608)
Disaster impact ( $t-1$ )	0.625* (0.343)	-1.560*** (0.544)	-24.18 (19.81)	-5.939 (4.419)
Disaster impact ( $t-2$ )	-0.151 (0.169)	-0.911* (0.465)	24.06 (25.77)	0.185 (3.339)
Disaster impact ( $t-3$ )	-0.562** (0.210)	-0.629 (0.666)	20.62 (15.57)	-3.308 (3.458)
Population density (Log)	0.0251 (0.0290)	-0.0941 (0.0896)	4.675** (2.033)	-0.676 (0.498)
Women proportion	-0.0409 (0.826)			
Elderly proportion		0.152 (0.258)		
Foreigner proportion			-33.13 (32.54)	
Disability proportion				-13.46*** (4.615)
Employment rate	0.00223 (0.00180)	0.00242 (0.00347)	-0.0365 (0.0799)	0.0153 (0.0291)
GDP per capita	0.00105 (0.0135)	0.00654 (0.0193)	0.204 (0.277)	-0.0379 (0.0931)
Disaster recovery expenditure rate	-0.0592 (0.0374)	-0.133 (0.121)	11.55*** (2.974)	-0.950 (0.835)
NPO per capita	23.03 (14.09)	92.63*** (33.30)	-574.8 (710.8)	493.4* (254.5)
Constant	-0.0153 (0.453)	0.0655 (0.132)	-5.438* (2.855)	1.619** (0.797)
Observations	782	782	782	782
$R^2$	0.082	0.079	0.071	0.095
Number of prefectures	46	46	46	46
Within $R^2$	0.0817	0.0792	0.0711	0.0950
Between $R^2$	0.0956	0.0573	0.137	0.000123
Overall $R^2$	0.00611	0.0247	0.0175	0.00210
Year effect	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

\*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$

correlate with reduced discrimination against women and the elderly, and no measurable changes in terms of foreigners and the disabled.

As with any study, our results should be viewed in terms of the limitations of our analysis. As we used prefectural level data for analyses, small-scale disasters, which only affect

a small area in the prefectures, may not measurably influence discrimination at the prefectural level. Therefore, only large-scale disasters that influence the whole prefecture may alter the cases of discrimination.

Next, given the broad, multi-year and multi-disaster scope of our research, we were only able to include data on vulnerable groups categorized according to a single characteristic, such as age, disability, immigrant status, and so on. More work is needed to understand the intersection of categories such as foreign women with disabilities, elderly women and other combinations of these traits. For example, whether such intersections lead to higher or lower levels of discrimination remains an unanswered question. Further, it is clear that individuals may be able to move out of the category of vulnerability—such as an immigrant or foreigner—over time, and our data are provided only in snapshot form.

Finally, we have used data from all prefectures (the equivalent of states in Japan) for a 17-year period, and the data are quite representative of recent social conditions in an advanced, industrialized democracy, we cannot make any claims about these patterns outside Japan, whether developed or developing, democratic or autocratic. We hope that other scholars will look to begin comparative studies of how shocks and disasters may change the social environment for vulnerable groups, that is, individuals who already regularly suffer disproportionate burdens during disasters.

Despite any limitations, our findings were robust to model type, lag, and the inclusion of a variety of controls. That is, we are confident that we have identified a pattern where disasters tend to reduce reported discrimination against vulnerable groups over time. We believe that shocks created a recognition of the precarious situation for vulnerable groups, perhaps through media coverage of tragedies involving the elderly and infirm or personal exposure to the challenging experiences of vulnerable friends and members of connected social networks. This recognition allowed for a broader altruism that other scholars have noted after the disasters which we see now extends not only to majority demographic groups (Solnit 2009), but also to vulnerable groups. At a time when natural hazards and shocks are likely to continue to grow in strength and number, our findings provide support for optimism that these disasters may help societies become more open to and engaged with vulnerable groups.

## Compliance with ethical standards

**Conflict of interest** There is no conflict of interest with this study.

## Appendix

See Table 6.

**Table 6** Data sources

Variables	Source
Discrimination against women, elderly people, foreigners and disability	From The Human Right Violations (Jinken Shinpan Tōkei) published by Japanese Ministry of Justice (Hōmushō) ( <a href="http://www.moj.go.jp/housei/toukei/toukei_ichiran_jinken.html">http://www.moj.go.jp/housei/toukei/toukei_ichiran_jinken.html</a> )
Disaster-affected household number	From the White Paper on the Fire Service (Shōbōhakusho) published by Disaster Management Agency (Shōbōchō) ( <a href="https://www.fdma.go.jp/publication/#whitepaper">https://www.fdma.go.jp/publication/#whitepaper</a> )
Household number	From The National Survey on Household Change (Setai Dotai Chōsa) published by the National Institution of Population and Social Security Research ( <a href="http://www.ipss.go.jp/site-ad/index_Japanese/cyousa.html">http://www.ipss.go.jp/site-ad/index_Japanese/cyousa.html</a> )
Total population	From the Japan Statistical Yearbook (Nihon Tōkei Nenkan) published by Statistics Bureau of Japan ( <a href="https://www.stat.go.jp/data/index.html">https://www.stat.go.jp/data/index.html</a> )
Area	From the Research of Prefecture Area (Zenkoku Todōfukuken Shikuchōsonbetsu Mensekichō) published by Geospatial Information Authority of Japan ( <a href="https://www.gsi.go.jp/KOKUJYOHO/MENCHO-title.htm">https://www.gsi.go.jp/KOKUJYOHO/MENCHO-title.htm</a> )
Population of women, elderly people and foreigners	From the Japan Statistical Yearbook (Nihon Tōkei Nenkan) published by Statistics Bureau of Japan ( <a href="https://www.stat.go.jp/data/index.html">https://www.stat.go.jp/data/index.html</a> )
Population of disabilities (Including physically handicapped persons, mentally handicapped persons and cerebrally handicapped persons)	From the Report on Social Welfare Administration and Services (Fukushi Gyōsei Hōkokurei) published by Ministry of Health, Labour and Welfare ( <a href="https://www.e-stat.go.jp/stat-search/files?tstat=000001034573">https://www.e-stat.go.jp/stat-search/files?tstat=000001034573</a> )
GDP (Gross Domestic Product)	From the Statistics on Economy of Citizens (Kenmin Keizai Seisan) published by Cabinet Office of Japan ( <a href="https://www.esri.cao.go.jp/jp/sna/data/data_list/kenmin/files/contents/main_h27.html">https://www.esri.cao.go.jp/jp/sna/data/data_list/kenmin/files/contents/main_h27.html</a> )
Disaster recovery expenditure	From the White Paper on Local Public Finance (Chihō Zaisei Hakusho) published by Ministry of Internal Affairs and Communications ( <a href="http://www.soumu.go.jp/menu_seisaku/hakusyo/index.html">http://www.soumu.go.jp/menu_seisaku/hakusyo/index.html</a> )
Non Profit Organization (NPO) number	From the Statistics of NPO (NPO Tokei Jyōhō) published by Cabinet Office, Government of Japan, NPO page ( <a href="https://www.npo-homepage.go.jp/about/toukei-info">https://www.npo-homepage.go.jp/about/toukei-info</a> )

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