LEARNING EFFECT AND SOCIAL CAPITAL: A CASE STUDY OF NATURAL DISASTER FROM JAPAN

yamamura, eiji

24 April 2008

LEARNING EFFECT AND SOCIAL CAPITAL: A CASE STUDY OF NATURAL DISASTER FROM JAPAN

Eiji Yamamura

Department of Economics, Seinan Gakuin University, 6-2-92 Sawaraku Nishijin Fukuoka 814-8511, Japan

Abstract.

Using Japanese prefecture level data for the years between 1988 and 2001, this paper explores how and the extent to which social capital has an effect on the damage resulting from natural disasters. It also examines whether the experience of a natural disaster affects individual and collective protection against future disasters. Using regression analysis and controlling for various factors such as the proportion of poor people, per capita income, and the number of natural disasters, there are three major findings. (1) Social capital reduces the damage caused by natural disasters. (2) The risk of a natural disaster makes people more apt to cooperate and therefore social capital is more effective to prevent disasters. (3) Economic conditions such as the level of income distinctly affect any damage, but hardly influence it when the scale of a disaster is small.

Keywords: Social Capital, Learning, Natural disaster

JEL classification: H41, P16, Z13

1. Introduction

A growing number of empirical works in the social sciences, including economics, have attempted to investigate issues regarding natural disasters (e.g., Albala-Bertland 1993, Burton et al. 1993, Garret & Sobel 2003, Tol & Leek 1999)[1]. One feature of natural disasters is that they appear to be caused by natural conditions and cannot be perfectly forecasted. This obviously leads to possible economic risks. Hence, Sawada and Shimizutani (2007) explored consumption insurance against natural disasters. Such an exogenous shock is likely to have tremendous effect on the degree of investment in physical and human capital, thereby affecting economic growth (Kellenberg & Monbarak 2008; Skidmore & Toya, 2002). Because of these features, humans fail to control for the occurrence of a natural disaster. Recent research, however, provides evidence that the degree of economic development, captured by the quality of institutions, social heterogeneity, social capital, and per capita income, has an important effect on the outcomes of natural disasters, although it cannot prevent them (Anbarci et al., 2005; Burton et al., 1993; Escaleras et al., 2007; Kahn, 2005; Tol & Leek, 1999; Toya & Skidmore, 2007).

Public sector corruption leads contractors to ignore a country's building codes and so buildings often fall short of the appropriate construction standards. This is a reason why public sector corruption is positively associated with earthquake deaths (Escalera et al., 2007). Institutional quality seems to be reflected in the degree to which a country is based on democracy. The evidence presented by Kahn (2005) shows that countries with a more democratic political system suffer less deaths from natural disasters. Anbarci et al. (2005) suggests, based upon economic theory, that collective action plays a critical role in saving lives when a natural disaster occurs; therefore, economic inequality hampers collective action and has a detrimental effect on disaster damage. On the other hand, social capital is likely to promote people to participate in civic life and so take collective action, resulting in economic benefit[2]. Social capital is found to be more easily formed in a society where economic and ethnic heterogeneity is smaller (Alesina & La Ferrara, 2000; Costa & Kahn, 2003; Vigdor, 2004, Yamamura 2008b)[3]. 'Social capital may mitigate

---

[1] As well, a growing number of reports on hurricane Katrina have been published (e.g., Congleton 2006, Shughart II 2006, Sobel and Leeson 2006, Ewing et al. 2007, Landry 2007, Chappell 2007, Boettke 2007, Whitt and Wilson 2007, Eckel 2007).

[2] A number of reports have attempted to investigate social capital (Berggren & Jordahl 2006, Knack & Keefer 1997, Putnam 2000).

[3] Generalized trust profoundly associated with social capital also depends on the

neighborhood instability and promote neighborhood cohesion' (Kan 2007, p. 437). As a result, social capital is expected to mitigate the damage caused by disasters via the enhancement of collective action. Little attention has, however, been given to the role of social capital on the alleviation of damage from a natural disaster.

Prior to natural disasters, people with a great amount of relevant information are less likely to suffer serious damage than those with less knowledge. Reports (Jovanovic, 1982; Jovanovic & Narko, 1996; Lucas, 1993) note that learning from past experience possibly enhances the accumulation of human capital, leading to economic growth. The argument of Jovanovic (1982) that a corporate entity knowing the optimal cost structure based upon a Bayesian learning process is similar in that an economic entity can more efficiently allocate resources through its experience. Such a learning mechanism is also considered to be applicable to the way natural disasters are dealt with. That is to say, people who have experienced natural disasters can obtain correct information about protecting against such events or getting out of them (Anbarci et al., 2005; Escaleras et al, 2007).

Experience of disasters appears to be helpful for mitigating disaster damage, not only at individual and government levels, but also at the community level. People seem to learn from their experiences of disasters and obtained relevant information about how a community member can take collective action to protect against them, and how the degree to which cooperative behavior benefits an individual by reducing damage. Therefore, prior information about protection against disasters is considered to have an important effect on the efficacy of social capital to reduce disaster damage. Nevertheless, studies dealing with the determinants of damage arising from natural disasters do not pay much attention to how social capital is associated with the collective learning effect. The purpose of this paper is to examine the extent to which social capital and the experience of natural disasters reduce damage. As well, it examines whether experience leads social capital to be more effective in mitigating damage. Furthermore, although Japan is a developed country, Japan society remains relatively homogeneous and social capital deeply accumulated; therefore, people are more inclined to take collective action (Yamamura, 2008b). Such a feature of Japan allows me to test how and the extent to which social capital is effective in a developed country.

The organization of this paper is as follows: Section 2 briefly surveys relationships between social capital and natural disasters, and advances a testable hypothesis. Section 3 presents a simple econometric framework. Section 4 discusses the results of the estimations. The final section offers concluding

---

features of the social structure (Leigh 2006a, 2006b, Bjørnskov, 2006).

observations.

2. Social capital and natural disasters

Occurrences of natural disasters are unequally distributed around the world. As they are over concentrated in some areas, the importance of disaster measures differs among countries. According to the Cabinet Office, Government of Japan (2007), 21 % of earthquakes of magnitude 6 and over occurred in Japan, although Japan landmass is only 0.25% of World's[4]. This implies that, compared with other countries, Japan should frequently suffer earthquake related natural disasters and therefore economic loss resulting from these should be recognizable. Therefore, protection against such damage is considered a central issue of economic policy. Compared to countries bordered by other ones, Japan's island condition is a natural limiting factor on the inflow of foreigners and influences from other cultures[5]. Therefore Japanese society continues to be relatively homogeneous. The more homogeneous a society is, the easier it is for collective action to take place and the more profoundly people trust each other (Alesina & La Ferrara, 2000; 2002). Ethnic and economic fragmentation are reported to have detrimental effects on damage arising from natural disasters, leading to increases in fatalities (Anbarci et al., 2003; Kahn, 2005). If this is the case, it is cogent to examine how Japan, characterized by a homogeneous society and frequent earthquakes, copes with natural disasters (Horwich, 2000; Sawada & Shimizutani, 2007)[6].

Information about how people and government become better at coping with

---

[4] Japan incurred 13 % of the total amount of damage resulting from natural disasters worldwide during the past 30 years (Cabinet Office, Government of Japan, 2007).

[5] Yamamura (2008b) indicated that the Hirfindahl-type index used of the ethnic fragmentation of Japan is 0.02. As suggested in Alesina et al. (2003), the value of Japan is smaller not only than that of the USA (0.49) but also the UK (0.12) characterized by the same island geography as Japan. A historical feature of Japan that illustrates an important difference from the UK should be considered to explain how the homogeneous Japanese character was formed. It is widely understood that the rulers of Japan during the Tokugawa period between 1639 and 1859 adopted a closed door policy (Sugiyama 1987). The policy of seclusion was initiated as a response to the perceived threat posed by Christian coverts in Japan. Such a policy aided by Japan's island geography is thought to have formed the fundamental homogeneous feature of Japanese society, which has persisted even after Japan opened up to world trade and to international exchanges.

[6] In Japan, social capital enhances learning from others such as from the diffusion of home computers (Yamamura, 2008a), makes a contribution to collective action such as responses to the Census (Yamamura, 2008b), and acts as informal deterrents against dangerously driving (Yamamura, 2008c).

disasters, an ability that is obtained through experience, is considered to play a critical role in mitigating the damage arising from a disaster (Anbarci.et.al., 2005; Escaleras et al., 2007). An example is the Kobe, Japan, earthquake "The earthquake struck a community, almost no member of which expected it. It has been almost a millennium since an event of comparative magnitude had occurred in the Kansai (Kobe-Osaka-Kyoto). Even business and agencies that had previously drawn up emergency plans were caught by surprise and were unable to implement them" (Horwich, 2000. p.529). Under such conditions, local government agencies were unprepared and so failed to coordinate the inflow of goods and services from outside the stricken area (Horwich, 2000). This was in part because of the lack of experience of a natural disaster in Kobe[7].

Delays in the initial response by the local government system were singled out for criticism in the aftermath of the Kobe Earthquake. On the other hand, much attention was given to role of the informal cooperative activity such as voluntary disaster control organizations in reducing the damage arising from that natural disaster. This is probably because voluntary organizations are thought to play important roles in coordinating collective action to reduce damage. An area where people are more inclined to participate in voluntary activity is hence considered to have deeply accumulated social capital (Putnam, 2000)[8]. There appear to be channels through which experiencing disasters affects social capital and thereby influences victims of disasters. An area that tends to regularly suffer from natural disasters has more inclination to diffuse information concerning preventive measures among its communities; therefore, it reinforces the functions of social capital to cope with risk through collective learning. As a consequence, social capital plays a greater role in mitigating damage from disasters if community members frequently experience such disasters[9]. From the discussion as above, two hypotheses can be derived:

Hypothesis 1: An area with highly accumulated social capital has a tendency to

[7] During the period of recovery from the Kobe earthquake, the city's fire department built a new observation and control center and its emergency management process has been reorganized and enlarged (Horwich, 2000).

[8] Putnam (2000) points out that social capital has a positive effect but also has a detrimental one upon human behavior. Durlauf (1999) asserts that social capital facilitates intragroup coordination by enhancing group identity, which, in turn, may promote intergroup hostility.

[9] It is also likely that social capital will make a community more resilient; that is, the community is more likely to recover quickly from a disaster. When hurricane Katrina occurred, the Catholic Church in New Orleans helped organize crews of returning residents to assist one another repairing homes (Boettke et al. 2007).

have less victims of natural disasters.

Hypothesis 2: Prior experience of disaster reinforces the function of social capital through a learning process, resulting in a reduction of victim numbers.

3. Data and method

3.1. Data and model

The data set used in this study is a survey panel of 47 prefectures covering 14 years from 1988 to 2001. Table 1 includes variable definitions, means, standard deviations, coefficients of variation, and maximums and minimums of analyzed data. The variables are discussed later. Number of victims, numbers of natural disasters, per capita income, number of fire fighting teams, and the number of immigrants are derived from Index Publishing (2006). Data about the numbers of natural disasters used in this research comprise the numbers of roads, bridges, banks that suffered from disasters and the numbers of landslides; all of which can be viewed as outcomes of earthquakes and hurricanes. Therefore, the magnitude of an earthquake and the intensity of a hurricane are considered to be reflected in the "number of disasters". There is wide range of intensities of natural disasters such as earthquakes and hurricanes. For instance, earthquakes occur every day but most are too weak to be perceived and therefore have no impact on people. Accordingly, I confront a difficulty in accurately counting natural disasters. The method of counting seems to affect the results and so cause an estimation bias. This is the reason why I considered observable outcomes of a "natural disaster" as disasters[10]. The total population number and the population subgroup over 70 years old, the number of those receiving public assistance, the number of policemen, the numbers of houses, public baths, and community centers, are from the Asahi Newspaper (2004). Some variables, including the numbers of public baths, community centers and fire fighting teams are divided by the population to obtain per capita values. The proportions of elderly and those receiving public assistance are calculated from the number over 70 years old, and the number receiving public assistance divided by the total population number, respectively.

There are several reports that have investigated fatalities in natural disasters (Anbarci et al. 2005, Escaleras et al. 2007, Kahn 2005); however, these

---

[10] The number of intense hurricanes and earthquakes can be obtained from National Astronomical Observatory Japan (2006). The similar results were provided when these data are used.

cover only a portion of the victims of disasters and so do not accurately reflect the full damage caused[11]. Thus this paper considers all victims as observed at the moment of an event. *VICTIM*, for which this paper attempts to examine determinants, is a non-negative count of victims of natural disasters. As such, a basic, and appropriate, estimation method is the poisson model. However, a shortcoming of the poisson model for this analysis is its assumption of an equal conditional mean and variance for the dependent variable. That is, to be appropriate in our case, the poisson model requires the conditional mean of *VICTIM* to be equal to its variance. As such, the poisson model is best applied in conditions where there is limited variation in the dependent variable. However, from Table1 it can be seen that maximum and minimum values are 62,085 and 0 respectively, and the standard deviation is 4,314, indicating the variation of the dependent variable is clearly a large one. As well, an over-dispersion of the number of victims is manifest in Table 2, showing the percentile rank. Numbers of victims in the lowest percentile, the 10^{th} percentile, is 1 whereas that of the highest is 1645. Taking table 1 into account, the mean value, 914, is above the 80^{th} percentile. Hence, careful attention must be paid to the over-dispersion of dependent variables when estimations are conducted. In such a situation, the use of a poisson process to estimate typically causes a downward bias in the model's standard errors. In line with reports concerning fatalities arising from natural disasters (Escaleras et al, 2007), a negative binominal model should be employed since this model generalizes the poisson process by expressly relaxing the assumption of an equal conditional mean and variance through the introduction of a parameter accounting for any unobserved heterogeneity between observations. What is more, using the zero-inflated negative binominal model introduces a splitting process, thus considering a zero victims account (Kahn(2005). Estimation by the zero-inflated negative binominal model uses a logit where the dependent variable equals 1 if there is no victim arising from a disaster. The logit model includes the number of natural disasters in year *t* and the interaction of its account with income.

3.2 Function form

Following the discussion above, the estimated function of the number of victims then takes the following form[12]:

---

[11] Toya & Skidmore (2007) explored not only fatalities but also the index of economic damage measured by the estimated damage in real US $ when disasters occurred.

[12] Values of coefficients can be interpreted as the elasticity of the number of victims with respect to the corresponding independent variables, which are evaluated at the sample mean values of the variables.

$$VICTIM_{it} = \alpha_0 + \alpha_1 NDIS_{it} + \alpha_2 AVDIS_{it} + \alpha_3 PBATH_{it} + \alpha_4 PBATH_{it} * AVDIS_{it} + \alpha_5 CENTE_{it} + \alpha_6 CENTE_{it} * AVDIS_{it} + \alpha_7 FFIGHT_{it} + \alpha_8 FFIGHT_t * AVDIS_{it} + \alpha_9 POLIC_{it} + \alpha_{10} IMIG_{it} + \alpha_{11} POP_{it} + \alpha_{12} PORAT_{it} + \alpha_{13} OLDRAT_{it} + \alpha_{14} INCOM_{it} + + \nu_t + \omega_{it},$$

where *VICTIM* represents the number of victims in prefecture *i* in year *t*, and α's represents the regression parameters. ν_t represent the unobservable specific effects of year *t* (a fixed effect time vector)respectively; ω_{it} represents the error term.

As mentioned, the structure of the data set used in this study is a survey panel of 47 prefectures covering the 14 years from 1988 to 2001. Macroeconomic conditions will be captured in ν_t, and I incorporate each year's dummy variables to restrain the time specific effects.

Though it seems obvious, it needs noting that an area can only contain victims of natural disasters if a natural disaster actually takes place there. Following Kahn(2005), in the logit model of the splitting stage where the number of disasters that a prefecture *i* experiences in year *t* and its interaction term of the log form of per capita income and population size, which are represented as *NDIS, NDIS*Ln(INCOME)* and *NDIS*Ln(POP)* respectively, are incorporated as independent variables. The interaction term of a disaster's count with income level and population would account for the possibility that prefectures with higher incomes and smaller populations are less inclined to suffer victims from disasters that occur. *NDIS*INCOME* and *NDIS*POP* are thus expected to take positive and negative signs since the logit model estimates the probability that nobody in a given prefecture in a given year becomes a victim of a natural disaster.

I now proceed to discuss determinants of the number of victims. The number of disasters, represented as *NDIS*, in year *t* and in prefecture *i* convincingly increases the number of victims and therefore takes a negative coefficient sign. As earlier discussed, people who experience disasters are better able to acquire information useful for preventing the effects of natural disasters, and so to reduce damage through leaning processes. To test this hypothesis, *AVDIS*, the average number of disasters occurring in past years is included as an explanatory variable to capture disaster experience[13]. The choice of the past years seems to have an effect upon the outcomes of estimation. If the prediction is supported, the sign of *AVDIS* becomes

[13] Cabinet Office, Government of Japan. (2007) reports that the past experience of disasters encourage people to take precautions against future disasters, whereas the effect of experience on cautious behavior diminishes as time passes. Therefore, this paper restricts past experiences to those within three years.

negative. To check the robustness of the results, I use three alternative variables (1) number of disaster occurring in the past year, namely, years t-1 in prefecture i, (2) the average number of disasters occurring from years t-1 to t-3 in prefecture i, (3) the average number of disasters occurring from years t-1 to t-5 in prefecture i. Furthermore, the importance of the experience of a natural disaster seems to change as time passes. These alternative variables also allow me to examine how and the extent to which passing time affects residents' behavior against a natural disaster.

The following independent variables are used as proxies of social capital. In traditional Japanese daily life, public baths were used by community members who, apart from the wealthy, ordinarily lived in houses without a private bath. Through the use of such baths people could get acquainted with neighbors and generate a social network. In modern Japan, most residences have their own baths, and people are therefore more likely to take a bath at home. However, a new type of public bath featuring more deluxe baths and saunas has recently developed, and these are used by all sectors of society, thus providing a place to meet neighbors and form social capital (Yamamura 2008a). The number of public baths, represented as *PBATH,* can thus serve as a proxy for social capital. Therefore, the signs of *PBATH* are predicted to be negative. People are more likely to trust each other and then take collective action if there is a place where they can communicate with each other and if the community is well organized (Putnam, 2000). *CNETE*, which is the number of community centers, is a proxy for social capital. Hence, the signs of *CENTE* are expected to be negative.

Earthquakes, as one of their results, are likely to entail fires as secondary events. Modern Japanese society is rooted in a system of group responsibility within a community. For instance, the community fire-fighting team, represented as *FFIGHT* originated in the Edo period and continues today (Goto 2001). Community fire-fighting teams, informal institutions, are still called for today because of the scarcity of public firehouses, which are regarded as formal institutions, and hence act as substitutes for public firehouses. What is more, these teams play an important role, not only in deterring fire but also in generating social capital through interpersonal communication in a cooperative protective activity against disaster (Goto 2001). Hence, fire-fighting teams are thought to have an important disaster prevention role. Members belonging to such teams also regularly patrol within their community to ensure that precautions are taken against fire; thereby keeping an eye on the streets, buildings and houses within their community. As a result of such activity, communal fire-fighting teams also function as a vigilant corps so that criminal behavior such as robbery, which is likely to occur after a disaster, is prevented[14]. As a consequence, the signs of *FFIGHT* are expected to be negative.

As noted before, experience of a natural disaster provides useful information concerning protection against future natural disasters, and then reinforces the function of social capital to take collective action to mitigate damage from a disaster. To test this hypothesis, which is the primary focus of this paper, cross terms between proxies of social capital and experience of disasters need to be checked. That is to say, the signs of *PBATH*AVDIS, CENTE*AVDIS* and *FFIGHT*AVDIS* are given careful attention and are predicted to become negative.

Police are considered to be the emergency first responder to a natural disaster and therefore *POLIC* is expected to take negative sign. Frequent movers weaken community ties; therefore, communities with higher rates of residential turnover are less well integrated. This is why residential mobility tends to undermine community-based social capital (Putnam, 2000); thereby hampering the collective action required to alleviate damage from a disaster. Hence, it is possible that the coefficients of *IMIG*, which is the number of immigrants from other prefectures arriving during the last year, take a positive sign.

The number of victims is expected to become larger in areas where a larger number of residents live if the scale of the natural disasters is of the same magnitude. Accordingly, the sign of *POP* representing total population is predicted to become positive. Lower income people are more likely to suffer from a natural disaster since they appear to live in more humble residences. The proportion of poor people thus increases the number of victims of disasters. In Japan, individuals living below a poverty threshold can be in receipt of public assistance so that the proportion of those who are in receipt of public assistance, which is denoted as *PORAT*, is regarded to proxy for the poor people rate. In addition, it seems reasonable that elderly people cannot make a quick response in an emergency, leading them to become victims. *OLDRAT*, which stands for the proportion of those over 70 years old, is incorporate to capture such an effect. Accordingly, *PORAT* and *OLDRAT* will also take a positive sign.

INCOM, representing per capita income is used to capture economic conditions. The number of victims is expected to become larger in areas where a larger number of residents live if the scale of the natural disasters is of the same magnitude. Areas with higher income are convincingly more able to build earthquake resistant

[14] Lederman et al (2002) uses international data to examine the social capital effect upon crime and suggests that countries with larger social capital are more apt to have reduced crime rates.

buildings and provide anti-earth quake equipment. Accordingly, the signs of *INCOM* are predicted to become negative.

IV. RESULTS

Tables 3 and 4 present the results of the zero inflated negative binominal estimations. In both tables, columns (1), (4), (7), and (10) show the results when the number of disasters occurring in the past year is used as *AVDIS.* Columns (2), (5), (8) and (11) show the results when the average number of disasters occurring in the past three years is used as *AVDIS.* Columns (3), (6), (9) and (12) show the results when the average number of disasters occurring in the past five years is used as *AVDIS.* To properly compare the results, values presented in the upper panel are the elasticity, which is evaluated at the sample mean values of the dependent and each independent variable. The results of Table 3 were estimated using all samples, 658 observations. As explained before, the zero inflated negative binominal model is employed to take into account the effect of outliers; thus it seems reasonable to ask whether the outcomes of estimations are at least somewhat influenced by outliers. As discussed for Tables 1 and 2 in the previous section, the sample is indeed skewed. To take this into account and to check the robustness of the outcome presented in Table 4, re-estimations are conducted when samples are restricted to those under 100 victims and therefore the observations become 356.

4.1. Logit estimation

In the bottom part of both tables, the results of the logit model of the splitting stage are reported. The cross term of *NDIS* and *POP* shows a negative sign for the coefficient in all estimations. Furthermore, the results of Tables 3 and 4 indicate statistical significance at the 1 % level in all estimations. Although contrary to the prediction, the signs of the cross terms of *NDIS* and *INCOM* become negative, but are not statistically significant in all estimations. Overall, these results are consistent with the prediction that larger population areas are more likely to have victims when a disaster occurs.

4.2. Estimation results using all samples

I now discuss the results of the negative binominal model after the splitting stage in Table 3. The significant positive signs of *NDIS* in all estimations of Table 3 are compatible with the prediction. With respect to *AVDIS,* all results show negative signs. As shown in the second row of columns (1) and (2), the fact that *AVDIS* is statistically significant, reveals that the learning effect makes a contribution to decreasing the number of victims. Nevertheless, column (3) is insignificant statistically, and its absolute value of 0.02 is remarkably smaller than those of (1) and (2). It follows from this that past experience reduces victim numbers but its effect diminishes as time passes.

With respect to the proxies for social capital, in columns (1), (2) and (3), *CENTE* , *PBATH* and *FFIGHT* take the anticipated negative sign of *CENTE*. In particular, *CENTE* is significant at the 1 % level. This indicates that social capital alleviates damage from disasters. Any insignificance of *PBATH* and *FFIGHT* are likely to be driven by potential shortcomings such as the skewness of the sample caused by outliers[15]. To investigate the learning effect through the experience of a disaster on the effectiveness of social capital, I check the results of the cross term of *AVNDIS* with proxies of social capital such as *PBATH*AVNDIS, CNETE*AVNDIS* and *FFIGHT*AVNDS*. As predicted previously, in all the of the interaction terms, their signs become negative. They become statistically significant when past experience is measured by the number of disaster occurring in the past year and in the past three years, but they become insignificant in the case using the number in the past five years. Furthermore, as shown in column (6), the absolute value of *PBATH * AVDIS*, which is 0.01 for both, is distinctly smaller than in columns (4) and (5), which are 0.06 and 0.04, respectively. The same tendency is observed concerning *CENTE * AVDIS* in columns (7)-(9) and *FFIGHT * AVDIS* in columns (10)-(12), indicating that the absolute values when *AVDIS* is calculated by the natural disasters in the past five years are by far smaller than the other values. Restricting attention to the results in the case that *AVNDIS* is calculated by data of the past year and the past three years, the absolute values of *AVDIS* and its interaction terms are between 0.04 and 0.08, indicating their elasticity is relatively modest. In line with the prediction, these results imply that the experience of a disaster accumulates the human capital necessary to protect against a future one; this then reinforces the function of social capital to coordinate collective action when a disaster occurs. Nevertheless, such an interaction effect has a tendency to disappear as time passes.

Contrary to the prediction, the signs of *POLIC* become positive, though insignificant, meaning that the police did not make a contribution to a reduction of victims. In all estimations, the significant negative signs of *IMIG* suggested that a

---

[15] Another possible reason for their unpredicted can be found in the argument of Lederman et al. (2002), that the indicators of social capital they defined reflect both group-specific and society-wide social capital, which are expected to promote and reduce collective action, respectively. Therefore these opposite effects neutralize each other.

decay of social capital causes impediments to the success of collective action, thereby increasing the number of victims.

Consistent with the prediction, in all estimations, *POP* take significant predicted signs and their values are larger than 4. As well, *PORAT* and *OLDRAT* take their anticipated signs although *PORAT* are not significant; indicating that poor and old individuals are more inclined to suffer from disasters. *INCOM* take their significant predicted signs and their values are larger than 3. From this can be derived the fact that the economic condition tremendously affects on the number of victims. Especially, the fact that if income rises 1 %, the number of victims decreases by about 4 %; reflecting that areas with higher incomes can to a large extent afford to protect against disasters.

4.3. Estimation results with the victims restriction

The determinants of the number of victims appear to depend on the magnitude of the disaster, while the skewness of the sample seems to influence the results, as argued by Escaleras et al. (2007). For a closer examination to take into these issues into account, I re-estimated using the same model but in which samples were restricted to a number of victims smaller than 100[16]. These results are shown in Table 4. Looking at columns (1) and (2) reveals in regard to *AVNDIS*, as reported in the second row, significant negative signs and the value of the coefficient. Column (3) suggests insignificance and a smaller value. Turning to the effects of social capital as captured by *PBATH, CENTE*, and *FFIGHT*, with the exception of *PBATH*, the coefficient signs become negative. These results are almost the same when all samples are used, as discussed before. It follows from the results discussed so far that not only a learning effect but also social capital are negatively associated with the number of victims resulting from natural disasters.

Switching attention to columns (4)-(12), where the cross terms of disaster experience and social capital are reported, I next examine how the learning effect reinforces social capital. Consistent with the prediction, all signs of *PBATH*AVNDIS, CNETE*AVNDIS* and *FFIGHT*AVNDS* are negative, and are equivalent to those presented in Table 3. In terms of the absolute values of the coefficients shown in columns (4),(5), (7),(8),(10), and (11), *AVDIS* and its interaction terms are between 0.02 and 0.06, suggesting they are almost at the same level as in

[16] While the estimation results shown in table 3 are based on the zero-inflated negative binominal model designed to take into account the effect of outliers, it seems reasonable to question whether the outliers matter since the sample is skewed as mentioned previously.

Table 3. On the other hand, when I used *AVNDIS* calculated using data from the past five years, they are not statistically significant and the absolute values become pronouncedly smaller. Taken together, the impacts on disaster damage of learning, social capital and their interaction do not disappear even when the scale of natural disasters is small, so long as the focus is on disaster experiences limited to those within a few years. Put another way, these effects are stable regardless of which samples are used and so are not affected by the scale of a disaster. Hence, the estimation results concerning *Hypotheses 1* and *2* are robust under the different samples, indicating that *Hypotheses 1* and *2* are strongly supported. Nevertheless, it is very interesting to observe that these effects diminish strikingly when I take more distant past events into account. According to the Cabinet Office, Government of Japan (2007), people in Japan are likely to take measures to cope with a natural disaster immediately after they experience a disaster but cease from doing so as time passes. From this I derive the argument that the precautions against the risk of a disaster surge as an outcome of a disaster experience but then gradually decrease over time. The findings I have presented thus far are considered to reflect the feature of human behavior pointed out by the Cabinet Office, Government of Japan (2007) .

I found it interesting that the coefficients of *INCOM* in Table 4, contrary to expectations, take positive signs in all columns. Accordingly, in respect to the per capita income, there is remarkable difference from those reported in Table 3 showing negative significant signs. What is more, the coefficient values *INCOM* are smaller than 1.00; far smaller than those shown in Table3. I derived from this that economic conditions are not associated with disaster damage when disasters are small in scale. Combining the estimation results in Tables 3 and 4 indicates that the effects of economic conditions on disaster damage are affected by the restriction of samples. The fact that higher incomes are more likely to reduce the number of victims does not persist when samples are restricted to a small number of victims. I interpret these results as follows. According to the theoretical model developed by Anbarci et al. (2005), the per capita level of income increases the provability of collective action in the form of the creation and enforcement of building codes, appropriate professional licensing, and earthquake-sensitive zoning[17]. That is, areas where income is at a high level have more ability to cope with natural disasters, mainly through the intensification of physical structures such as the provision of earthquake-resistant buildings, fire proof-buildings, and/or

[17] The collective action required here is different from that required for informal voluntary activity promoted by social capital.

fire-prevention equipment. Such measures seem to be effective in alleviating the damage when inordinate scale disasters strike buildings. In the case where the magnitude of a disaster is, however, too modest to damage the physical structure, economic conditions such as per capita income do not affect outcomes.

To sum the evidence presented so far; factors concerning disaster experience and social capital for reducing disaster damage persist even with the different samples. However, per capita income has tremendous effects on any resulting damage, though this relationship disappears because of the restriction of our samples. The evidence above seems to indicate that informal cooperative activity promoted through accumulation of social capital plays an important role in alleviating disaster damage, especially in cases where the disaster is not of a large scale, being one in which economic factors can make no contribution to the reduction of damage.

5. Conclusion

It is impossible to control the occurrences of natural disasters, but it is possible to alleviate damage to some extent. An example is taking protection action against a future natural disaster; indeed, this is an area where local government is expected to assume an important role in coping with disasters. Nevertheless, the Kobe earthquake case in Japan shows what can go wrong; in that event, the initial response system of the local government organs was delayed and indeed malfunctioned, whereas informal cooperative activity such as voluntary disaster control organizations responded promptly, resulting in a reduction of the damage arising from this natural disaster. To reduce damage, collective action is called for and voluntary organizations are important. Therefore, informal organizations are likely to decrease damage through their collective action in areas where there is high social cohesion and therefore people are more inclined to participate in voluntary activities.

Through experiencing a natural disaster, individuals may learn the how to deal with a future natural disaster. As well, this experience is apt to change the attitude of individuals regarding disasters. As larger amounts of information concerning natural disasters are obtained, individuals are more likely to perceive latent damage resulting from a lack of appropriate measures, and therefore take steps to cope.

The main aim of this paper has been to examine how and the extent to which the experience of a natural disaster, social capital, and their interaction are related with damage resulting from natural disasters measured by the number of victims. To this end, using prefecture level data of Japan for the years between 1988 and

2001, this paper ascertained the determinants of the number of victims of natural disasters. The major findings from this study were: (1) Social capital reduces damage resulting from natural disasters. (2) Abundant information concerning natural disasters obtained through past experiences makes people more apt to cooperate and therefore social capital becomes more effective to prevent disasters. Nevertheless, it becomes less effective as time passes after the experience of a disaster. (3) A high level of income makes much more contribution than social capital to a reduction in the number of victims; nevertheless, the level of income hardly affects the number of victims in small scale disasters, hence social capital makes a greater contribution in this situation.

From the estimations here, I derived an argument that, in general, physical equipment and infrastructure against disasters are more effective than cooperative behavior, namely collective action, among people. By contrast, cooperative behavior becomes relatively more effective in small scale disasters. What is more, thanks to a spillover of information about natural disasters, cooperative behavior is thought to be more easily organized, thereby reducing the damage resulting from such a disaster. The positive effect of the disaster experience on cooperative behavior deteriorates as time passes after people experience a disaster, because people' decrease their precautions against a future disaster. It follows from this that a government should not only provide physical equipment, but should also make efforts to transmit more information about natural disasters to stimulate and promote collective action by it citizens against disaster.

This study uses aggregated-level data at a prefecture level and so individual responses to natural disasters cannot be considered. Further, I consider the experience of suffering disasters to be a proxy for the quantity of information about disasters obtained by people. This assumption, however, may not be sufficiently convincing. Accordingly, a more appropriate measure for the information acquired by people prior to disaster is called for. For a closer investigation of the findings in this paper, more purposefully constructed individual-level data needs to be used. These are issues remaining to be addressed in future study.

References

Albala-Bertrand, J., 1993., Political Economy of Large Natural Disasters. New York : Oxford University Press.

Alesina, A.,La Ferrara, E., 2000. Participation in heterogeneous communities. Quarterly Journal of Economics 115, 847-904.

Alesina, A., La Ferrara, E. 2002. Who trust others? Journal of Public Economics 85. 207-234.

Alesina, A., Devleeschauwer, A., Easterly, W., Kurlat, S., Wacziag, R. 2003. Fractionalization.. Journal of Economic Growth 8. 155-194.

Anbarci, N., Escaleras, M., and Register, C., 2005. Earthquake fatalities: the interaction of nature and political economy. Journal of Public Economics 89, 1907-1933.

Asahi Newspaper., 2004. Minryoku: TODOFUKEN-BETSU MINRYOKU SOKUTEI SHIRYOSHU (CD-ROM edition), Tokyo: Asahi-Newspaper.

National Astronomical Observatory Japan, 2006. RIKA NENKAN (Chronological Scientific Tables), Tokyo: National Astronomical Observatory.

Berggren, N., Jordahl, H. 2006. Free to trust: Economic freedom and social capital. Kyklos 59, 141-169.

Bjørnskov, C. 2006 Determinants of generalized trust: A cross-country comparison. Public Choice, 130, 1-21.

Boettke. P., Chamlee-Wright, E., Gordon, P., Ikeda, S., Leeson, P.T, and Sobel, R. 2007. The political, economic, and social aspect of Katrina. Southern Economic Journal 74, 363-376.

Burton, K., Kates, R., White, G. 1993. The Environment as Hazard, 2nd edition. New York: Guilford Press.

Cabinet Office, Government of Japan. A Disaster Prevention White Paper. (In Japanese) Cabinet Office, Government of Japan. 2007.http://www.bousai.go.jp/hakusho/h19/index.htm

Chappell, W. F., Forgette, R.G., Swanson. D.A., Van Boening. M.V., 2007. Determinants of government aid to Katrina Survivors: evidence from survey data. Southern Economic Journal 74, 344-362.

Congleton, R.D. 2006. The story of Katrina: New Orleans and the political economy of catastrophe. Public Choice 127, 5-30.

Costa, D., Kahn, M. 2003. Civic engagement in heterogeneous communities. Perspectives on Politics 1, 103-112.

Durlauf, S. 1999. The case 'against' social capital. Focus 20, 1-5.

Eckel, C., Grossman, P.J., Milano, A. 2007. Is More information always better? An experimental study of charitable giving and hurricane Katrina. Southern Economic Journal 74, 388-411.

Escaleras, M., Anbarci, N, Register, C. 2007. Public sector corruption and major earthquakes: A potentially deadly interaction. Public Choice 132, 209-230.

Ewing, B.T., Krusse, J.B., Sutter, D. 2007. Hurricanes and economic research: An introduction to the Hurricane Katrina Symposium. Southern Economic Journal 74, 315-325.

Garret, T., Sobel, R. 2003. The political economy of FEMA disaster Payments. Economic Inquiry 41, 496-509.

Goto, I. 2001. Tracing the origin of the communal fire-fighting team: Communal fire-fighting teams in the 21st century (Shobo-dan no Genkryu o Tadoru: 21seki no Shobo-dan no Arikata). Tokyo: Kindaishobo-sha.

Horwich, G. 2000. Economic lessons from the Kobe earthquake. Economic Development and Cultural Change 48, 521-542.

Index Corporation. 2006. Chiiki toukei 2006 (CD-ROM edition), Tokyo: Index corporation.

Japan Broadcasting Corporation (Nihon hoso kyokai). 1979, 1996 Zenkoku kenmin ishiki chosa.

Jovanovic, B. 1982. Selection and evolution of industry. Econometrica 50, 649-670.

Jovanovic, B., Nyarko, Y. 1996. Leaning by doing and the choice of technology. Econometrica 64, 1299-1310.

Kan, K. 2007. Residential mobility and social capital. Journal of Urban Economics 61, 436-457.

Kahn, M. 2005. The death toll from natural disasters: the role of income, geography, and institutions. Review of Economics and Statistics 87, 271-284.

Kellenberg, D.K., Mobarak, A. M. 2008. Does rising increase or decrease damage risk from natural disasters? Journal of Urban Economics 63, 788-802.

Knack, S. Keefer, P. 1997. Does social capital have an economic payoff? Public Choice 112, 1251-1288.

Landry, C.E., Bin, O., Hindsley, P., Whitehead, J.C., Wilson, K. 2007. Going home: Evacuation-migration decisions of hurricane Katrina survivors. Southern Economic Journal 74, 326-343.

Lederman, D., Loayza, N., Menéndez, M. 2002. Violent crime: Does social capital matter? Economic Development and Cultural Change 50, 509-39.

Leigh, A. 2006a. Does equality lead to fraternity? Economics letters 93, 121-125.

Leigh, A. 2006b. Trust, inequality, and ethnic heterogeneity. Economic Record 82, 268-280.

Lucas, R.E. 1993. Making a miracle. Econometrica 61, 251-272.

Putnam, R. 2000. Bowling alone: the collapse and revival of American community, A Touchstone Book, New York.

Sawada, Y., Shimizutani, S. 2007. Consumption insurance against natural disasters: Evidence from the Great Hanshin-Awaji (Kobe) earthquake. Applied Economics Letters 14, 303-306.

Shughart II, W. F. 2006. Katrinanomics: The politics and economics of disaster relief. Public Choice 127, 2006, 31-53.

Skidmore, M., Toya, H. 2002. Do natural disasters promote long-run economic growth. Economic Inquiry 40, 664-687.

Sobel, R.S., Leeson, P.T., 2006. Government's response to hurricane Katrina: A public choice analysis. Public Choice 127, 55-73.

Statistics Bureau of the Ministry of Internal Affairs and Communications. Zenkoku shohi zhittai chosa. Tokyo: Statistics Bureau of the Ministry of Internal Affairs and Communications, (various year).

Sugiyama, S. The impact of the opening of the ports on domestic Japanese industry: The case of silk and cotton. Economic Studies Quarterly 38, 338-353.

Tol, R., Leek, F. 1999. Economic Analysis of Natural Disasters. In: Downing, T., Olsthoorn, A., Tol, R. (Eds.), Climate Change and Risk. Routledge, London, 308-327.

Toya, H., Skidmore, M. 2007. Economic development and the impact of natural disasters. Economics Letters 94, 20-25.

Vigdor, J.L. 2004. Community composition and collective action: Analyzing initial mail response to the 2000 Census. Review of Economics and Statistics 86, 303-312.

Whitt, S., Wilson, R.K. 2007. Public goods in the field: Katrina evacuees in Houston. Southern Economic Journal 74, 377-387.

Yamamura, E. 2008a. Diffusion of home computers and social networks: A study using Japanese panel data. Forthcoming in Applied Economics Letters.

Yamamura, E. 2008b. The effects of inequality, fragmentation, and social capital on collective action in a homogeneous society: Analyzing responses to the 2005 Japan Census. Forthcoming in Journal of Socio-economics.

Yamamura, E. 2008c. The impact of formal and informal deterrents on driving behavior. Forthcoming in Journal of Socio-economics.

Table 1

Variable definitions and descriptive statistics

Variable	Definition	Mean	Standard deviation	Coefficient of variation	Max	Min
VICTIM	Number of victims	914	4314	4.71	62,085	0
NDIS	Number of natural disasters	91	262	2.85	4,898	0
AVNDIS (1 year)	Number of disasters during the past year.	102	289	2.83	4,898	0
AVNDIS (3 Years)	Average number of disasters during the past three years.	103	169	1.63	1,708	1
AVNDIS (5 Years)	Average number of disasters during the past five years.	124	270	2.17	3,516	1.6
PBATH	Per capita number of public baths	$0.21*10^{-3}$	$0.07*10^{-3}$	0.33	$0.49*10^{-3}$	$0.09*10^{-3}$
CENTE	Per capita number of community centers	$0.22*10^{-3}$	$0.17*10^{-3}$	0.77	$0.90*10^{-3}$	$0.07*10^{-3}$
FFIGHT	Per capita number of fire fighting teams	$0.31*10^{-3}$	$0.14*10^{-3}$	0.45	$0.62*10^{-3}$	$0.04*10^{-3}$
POLIC	Number of policemen	4,763	6,536	1.37	42,197	1,069
IMIG	Share of immigrants from other prefectures [a)]	$21*10^{-3}$	$5*10^{-3}$	0.26	$42*10^{-3}$	$10*10^{-3}$
POP	Population numbers[a)]	2,648	2,393	0.90	11,900	616
PORAT	The share of those receiving public assistance	$7.45*10^{-3}$	$4.52*10^{-3}$	0.606	$28.6*10^{-3}$	$1.77*10^{-3}$
OLDRAT	The share of elderly over 70 years old.	0.11	0.02	0.24	0.19	0.05
INCOM	Per capita income [b)]	2,838	408	0.14	4.813	1.915

Notes: a) expressed in thousands

b) expressed in thousands of yen.

Table 2.Distribution of victims

Percentile	
10	1
20	5
30	12.7
40	26.6
50	67
60	139
70	266
80	594
90	1645

Table 3　Determinants of the number of victims (Zero inflated negative-binominal model)

	(1) 1Year	(2) 3Years	(3) 5 Years	(4) 1 Year	(5) 3 Years	(6) 5 Years	(7) 1 Year	(8) 3 Years	(9) 5 Years	(10) 1 Year	(11) 3 Years	(12) 5 Years
NDIS	0.41**	0.42**	0.42**	0.41**	0.42**	0.42**	0.41**	0.42**	0.42**	0.41**	0.42**	0.42**
	(3.90)	(3.85)	(3.88)	(3.89)	(3.86)	(3.88)	(3.86)	(3.83)	(3.89)	(3.87)	(3.84)	(3.88)
AVNDIS	-0.05*	-0.06*	-0.02									
	(-1.95)	(-1.96)	(-1.02)									
PBATH	-0.004	0.06	0.02	0.09	0.11	0.02	0.06	0.08	0.001	0.04	0.08	0.01
	(-0.02)	(0.23)	(0.07)	(0.33)	(0.40)	(0.08)	(0.24)	(0.30)	(0.001)	(0.17)	(0.31)	(0.06)
PBATH* AVNDIS				-0.06**	-0.04*	-0.01						
				(-7.49)	(-1.96)	(-0.64)						
CENTE	-0.36**	-0.38**	-0.31*	-0.34**	-0.37**	-0.33*	-0.26*	-0.29*	-0.33*	-0.35**	-0.38**	-0.31*
	(-2.60)	(-2.72)	(-2.17)	(-2.54)	(-2.70)	(-2.23)	(-1.74)	(-2.14)	(-2.11)	(-2.60)	(-2.76)	(-2.13)
CENTE* AVNDIS							-0.05**	-0.07**	-0.003			
							(-2.95)	(-2.58)	(-0.37)			
FFIGHT	-0.12	-0.10	-0.12	-0.13	-0.11	-0.13	-0.16	-0.12	-0.13	-0.06	-0.06	-0.10
	(-0.47)	(-0.37)	(-0.45)	(-0.49)	(-0.41)	(-0.48)	(-0.59)	(-0.44)	(-0.50)	(-0.26)	(-0.22)	(-0.39)
FFIGHT* AVNDIS										-0.08**	-0.05*	-0.02
										(-8.81)	(-2.24)	(-0.99)
POLIC	0.24	0.25	0.25	0.24	0.25	0.25	0.27	0.25	0.26	0.26	0.25	0.25
	(1.02)	(1.06)	(1.07)	(1.05)	(1.05)	(1.09)	(1.16)	(1.08)	(1.10)	(1.11)	(1.07)	(1.08)
IMIG	0.84*	0.93*	0.85*	0.87*	0.90*	0.83*	0.84*	0.89*	0.81*	0.87*	0.92*	0.84*
	(2.15)	(2.31)	(2.15)	(2.21)	(2.25)	(2.09)	(2.13)	(2.25)	(2.04)	(2.21)	(2.28)	(2.12)
POP	4.47**	4.50**	4.44**	4.49**	4.43**	4.42**	4.58**	4.48**	4.41**	4.50**	4.44**	4.42**
	(4.46)	(4.54)	(4.46)	(4.54)	(4.49)	(4.44)	(4.62)	(4.55)	(4.43)	(4.54)	(4.50)	(4.43)
PORAT	0.31	0.29	0.32	0.32	0.30	0.32	0.32	0.28	0.33	0.29	0.28	0.32
	(1.41)	(1.29)	(1.40)	(1.43)	(1.30)	(1.49)	(1.44)	(1.25)	(1.45)	(1.31)	(1.23)	(1.40)
OLDRAT	1.60*	1.69*	1.64*	1.62*	1.72*	1.66*	1.59*	1.70*	1.67*	1.59*	1.72*	1.64*
	(1.67)	(1.76)	(1.70)	(1.70)	(1.79)	(1.73)	(1.66)	(1.77)	(1.73)	(1.67)	(1.79)	(1.70)
INCOM	-3.89**	-4.21**	-4.15**	-3.98**	-4.30**	-4.16**	-4.09**	-4.33**	-4.14**	-4.08**	-4.37**	-4.18**
	(-2.92)	(-3.21)	(-3.14)	(-3.05)	(-3.24)	(-3.13)	(-3.11)	(-3.29)	(-3.11)	(-3.12)	(-3.28)	(-3.16)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Logit Model												
NDIS	4.58*	4.59*	4.56*	4.51*	4.56*	4.58*	4.49*	4.49*	4.60*	4.51*	4.58*	4.56*
	(2.21)	(2.28)	(2.22)	(2.20)	(2.25)	(2.22)	(2.15)	(2.24)	(2.22)	(2.21)	(2.27)	(2.21)
NDIS* Ln(INCOM)	-0.22	-0.22	-0.21	-0.21	-0.22	-0.22	-0.20	-0.21	-0.22	-0.21	-0.22	-0.21
	(-0.83)	(-0.87)	(-0.83)	(-0.81)	(-0.85)	(-0.83)	(-0.76)	(-0.83)	(-0.84)	(-0.82)	(-0.87)	(-0.83)
NDIS* Ln(POP)	-0.21**	-0.21**	-0.21**	-0.21**	-0.21**	-0.21**	-0.21**	-0.21**	-0.21**	-0.21**	-0.21**	-0.21**
	(-2.77)	(-2.90)	(-2.88)	(-2.91)	(-2.90)	(-2.87)	(-2.91)	(-2.91)	(-2.86)	(-2.79)	(-2.90)	(-2.87)
α	2.57**	2.57**	2.57**	2.53**	2.53**	2.53**	2.53**	2.53**	2.53**	2.53**	2.53**	2.53**
	(45.8)	(45.8)	(45.8)	(45.9)	(45.9)	(45.9)	(45.8)	(45.8)	(45.8)	(45.8)	(45.8)	(45.8)
Samples	658	658	658	658	658	658	658	658	658	658	658	658
Non-zero samples	604	604	604	604	604	604	604	604	604	604	604	604

Notes: Each column of this table reports a separate estimate of a zero inflated negative binominal model. As discussed in the text, this model has two equations.　The lower panel of the table reports the logit model estimates of the probability that nobody becomes a victim of a natural disaster. The upper panel reports the results from the negative binominal regression where numbers are elastic and are evaluated at the sample mean values of the dependent and each independent variable, and values in parentheses are z-statistics calculated by the delta method using robust standard errors. * and ** denote significance at the 5% and 1% levels, respectively.　In each estimate, constants, year dummies, rates of primary industry populations, number of households, and hours of sunlight are included but not reported to save space

Table 4. Determinants of the number of victims (Zero inflated negative-binominal model) Number of victims<100

	(1) 1Year	(2) 3Years	(3) 5 Years	(4) 1 Year	(5) 3 Years	(6) 5 Years	(7) 1 Year	(8) 3 Years	(9) 5 Years	(10) 1 Year	(11) 3 Years	(12) 5 Years
NDIS	0.18	0.19	0.19	0.18	0.19	0.18	0.18	0.18	0.18	0.18	0.19	0.19
	(1.10)	(1.24)	(1.21)	(1.13)	(1.20)	(1.19)	(1.09)	(1.17)	(1.18)	(1.08)	(1.17)	(1.21)
AVNDIS	-0.03**	-0.07*	-0.01									
	(-3.66)	(-1.81)	(-0.66)									
PBATH	0.05	0.06	0.02	0.09	0.13	0.02	0.08	0.10	0.02	0.07	0.08	0.02
	(0.23)	(0.25)	(0.08)	(0.37)	(0.53)	(0.12)	(0.33)	(0.39)	(0.01)	(0.32)	(0.35)	(0.08)
PBATH AVNDIS*				-0.02**	-0.04*	-0.004						
				(-4.31)	(-1.99)	(-0.29)						
CENTE	-0.20*	-0.19*	-0.17	-0.19*	-0.17	-0.18	-0.15	-0.12	-0.18	-0.20*	-0.19*	-0.16
	(-1.79)	(-1.73)	(-1.42)	(-1.76)	(-1.57)	(-1.48)	(-1.34)	(-0.92)	(-1.47)	(-1.85)	(-1.72)	(-1.36)
CENTE AVNDIS*							-0.02*	-0.03	-0.001			
							(-1.87)	(-0.91)	(-0.21)			
FFIGHT	-0.22	-0.21	-0.22	-0.22	-0.23	-0.22	-0.22	-0.22	-0.22	-0.19	-0.15	-0.21
	(-1.17)	(-1.14)	(-1.16)	(-1.19)	(-1.22)	(-1.17)	(-1.15)	(-1.18)	(-1.17)	(-1.00)	(-0.80)	(-1.09)
FFIGHT AVNDIS*										-0.03**	-0.06**	-0.01
										(-5.87)	(-2.83)	(-0.86)
POLIC	-0.17	-0.16	-0.17	-0.17	-0.17	-0.17	-0.16	-0.16	-0.17	-0.17	-0.16	-0.17
	(-1.36)	(-1.28)	(-1.32)	(1.39)	(-1.36)	(-1.33)	(-1.32)	(-1.28)	(1.33)	(-1.39)	(-1.28)	(-1.32)
IMIG	0.05	0.04	-0.02	0.04	0.03	-0.01	0.03	0.01	-0.01	0.07	0.07	-0.02
	(0.18)	(0.15)	(-0.08)	(0.15)	(0.13)	(-0.06)	(0.12)	(0.06)	(-0.06)	(0.25)	(0.23)	(-0.08)
POP	1.43*	1.59**	1.31*	1.36*	1.48*	1.29*	1.40*	1.48*	1.28*	1.38*	1.58**	1.30*
	(2.23)	(2.43)	(2.07)	(2.13)	(2.31)	(2.03)	(2.22)	(2.25)	(2.01)	(2.19)	(2.47)	(2.06)
PORAT	0.14	0.14	0.14	0.13	0.14	0.13	0.13	0.14	0.13	0.12	0.13	0.14
	(1.05)	(1.05)	(1.01)	(0.97)	(1.01)	(0.99)	(0.98)	(1.01)	(0.98)	(0.92)	(0.94)	(100)
OLDRAT	-1.00	-1.05	-1.12	-1.01	-1.05	-1.09	-1.07	-1.12	-1.08	-1.01	-1.06	-1.14
	(-1.41)	(-1.47)	(-1.52)	(-1.41)	(-1.46)	(-1.48)	(-1.50)	(-1.53)	(-1.48)	(-1.43)	(-1.49)	(-1.55)
INCOM	0.77	0.86	0.80	0.68	0.76	0.75	0.73	0.79	0.74	0.68	0.78	0.80
	(0.69)	(0.77)	(0.71)	(0.62)	(0.69)	(0.67)	(0.66)	(0.71)	(0.67)	(0.61)	(0.70)	(0.71)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
						Logit Model						
NDIS	2.86*	2.95*	2.87*	2.85*	2.85*	2.86*	2.79*	2.81*	2.86*	2.85*	2.90*	2.58*
	(1.83)	(1.86)	(1.87)	(1.84)	(1.85)	(1.82)	(1.83)	(1.83)	(1.82)	(1.84)	(2.27)	(1.81)
NDIS Ln(INCOM)*	-0.45	-0.05	-0.04	-0.04	-0.04	-0.04	-0.03	-0.03	-0.04	-0.04	-0.04	-0.04
	(-0.17)	(-0.19)	(-0.15)	(-0.16)	(-0.16)	(-0.15)	(-0.13)	(-0.13)	(-0.15)	(-0.18)	(-0.18)	(-0.15)
NDIS Ln(POP)*	-0.18**	-0.19**	-0.19***	-0.18**	-0.19**	-0.19**	-0.18**	-0.19**	-0.19**	-0.18**	-0.18**	-0.19**
	(-2.44)	(-2.41)	(-2.42)	(-2.46)	(-2.44)	(-2.43)	(-2.45)	(-2.42)	(-2.43)	(-2.46)	(-2.43)	(-2.42)
α	2.57**	2.57**	2.57**	2.53**	2.53**	2.53**	2.53**	2.53**	2.53**	2.53**	2.53**	2.53**
	(45.8)	(45.8)	(45.8)	(45.9)	(45.9)	(45.9)	(45.8)	(45.8)	(45.8)	(45.8)	(45.8)	(45.8)
Samples	355	355	355	355	355	355	355	355	355	355	355	355
Non-zero samples	301	301	301	301	301	301	301	301	301	301	301	301

Notes: Each column of this table reports a separate estimate of a zero inflated negative binominal model. As discussed in the text, this model has two equations. The lower panel of the table reports the logit model estimates of the probability that nobody becomes a victim of a natural disaster. The upper panel reports the results from the negative binominal regression where numbers are elastic and are evaluated at the sample mean values of the dependent and each independent variable, and values in parentheses are z-statistics calculated by the delta method using robust standard errors. * and ** denote significance at the 5% and 1% levels, respectively. In each estimate, constants, year dummies, rates of primary industry' populations, number of households, and hours of sunlight are included but not reported to save space