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Yasuyuki Sawada, Keiko Iwasaki and Toyo Ashida

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by

Yasuyuki Sawada*
University of Tokyo and Asian Development Bank

Keiko Iwasaki
NLI Research Institute

Toyo Ashida
University of Tokyo

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Abstract

Disasters affect livelihoods and preferences. We investigate the relationship between damage caused by a disaster and individual hyperbolic discounting, adopting sui generis data from two communities hit by the Great East Japan Earthquake of 2011： Iwanuma and Futaba, where exposure to a disaster aggravates an individual's present bias captured in elementary or junior high school. This causal relationship is a key mechanism behind the disaster and depression nexus. Our results suggest the need to provide commitment devices to mitigate harmful outcomes induced by aggravated hyperbolic discounting resulting from disaster exposure, thus shedding new light on disaster rehabilitation policies.

Keywords: disaster; preference; present bias; hyperbolic discounting
Journal of Economic Literature (JEL) Classification Codes: D91; H84

***Corresponding author**

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I. Introduction

Exposure to a variety of natural disasters undermines people's socioeconomic well-being both directly and indirectly, as several studies show the nexus between disasters and economic growth (Barro 2006, 2009; Cavallo et al. 2013; Cavallo and Noy 2011; Kellenberg and Mobarak 2011; Noy 2009; Skidmore and Toya 2002; Toya and Skidmore 2007).[1] Since disasters substantially traumatize individuals, exposure to them can also cause mental distress (Van Griensven et al. 2006; Kumar et al. 2007; Frankenberg et al. 2008; Fergusson et al. 2014; Tsuboya et al. 2016; Iwasaki, Sawada, and Aldrich 2017). The impact of natural catastrophes on mental conditions implies that disaster exposure might not only affect survivors' overall economy and livelihoods, but also their preferences. Individual risk and time preference parameters may play a critical role in establishing the disaster exposure and mental health nexus, because these preferences constitute the basis for an individual's and society's response toward market price changes for damaged goods and shifts in interpersonal relationships. In this respect, recent economic studies on individual risk attitudes have demonstrated that the socioeconomic environment determines individual and social preferences (Outreville 2014), and that calamities can alter individual preferences in terms of risk and time delays.[2]

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[1] In recent times, there has been a significant global rise in the number of natural disasters, which undermine the sustainable development of the world economy (Aldrich, Oum, and Sawada 2014; Cavallo and Noy 2011; Kellenberg and Mobarak 2011; Strömberg 2007).

[2] See, for example, Chuang and Schechter (2015) and Sawada (2015). However, they provide mixed results on how they alter these preference parameters. While many studies have shown that natural disasters can change risk attitudes, making people more risk averse (Cameron and Shah 2015; Cassar, Healy, and von Kessler 2017; Chantarat et al. 2015; Samphantharak and Chantarat 2015), several other investigations have revealed that calamities can make individuals more risk tolerant (Eckel, El-Gamal, and Wilson 2009; Hanaoka, Shigeoka, and Watanabe 2018). Regarding the timing of preference parameters, Cassar, Healy, and von Kessler (2017) found an increased time discount rate during the 2004 tsunami in Thailand. Furthermore, by examining the 2011 floods in the Philippines and those that occurred during the Great East Japan Earthquake, Sawada and Kuroishi (2015a, 2015b) discovered that witnessing a natural disaster makes individuals have more present bias than those unaffected. On the other hand, a decreased time discount rate has been found in studies on the tsunami in Sri Lanka among wage earners (Callen 2015) and in studies on the 2011 flood in Cambodia among rice farmers (Chantarat et al. 2015). Furthermore, some research examines the impacts of man-made calamities (such as economic crises and civil conflicts) on individual preference parameters. Using Finnish data, Knüpfer, Rantapuska, and Sarvimäki (2013) found that a severe recession made people risk averse, while Kim and Lee (2014) indicated that individuals who were four to eight years old

In this paper, we focus on how disaster damage affects individual present bias, considering the following three issues. First, present bias is closely connected to critical harmful behavior exhibited by disaster victims (e.g., over-borrowing, gambling, and overeating). In this way, disasters undermine people's livelihoods. Second, present bias is an essential behavioral parameter in determining risk attitude, as some recent theoretical works reveal (Halevy 2008; Saito 2011, 2015). Thirdly, the disaster and present bias nexus has rarely been investigated in the literature.[3]

To this end, we adopt sui generis data collected from two communities seriously affected by the Great East Japan Earthquake of March 11, 2011: the city of Iwanuma, which was struck by the tsunami, and the town of Futaba, which was impacted by both the tsunami and the nuclear power plant failure. Through original surveys, we obtain information on the pre-disaster level of present bias when respondents were in elementary or junior high school, as well as the post-disaster level of present bias, together with each respondent's level of disaster exposure. These unique datasets allow us to investigate the impact of disaster exposure on the long-term stability of present bias. Moreover, differences between Iwanuma and Futaba within the context of disaster exposure can help to verify the external validity of our findings.

To preview our results, we found that exposure to disasters aggravates an individual's present bias, captured in elementary and junior high school in both places. Also, our empirical results provide supporting evidence in which the causal relationship between disaster exposure and present bias is a key mechanism behind the disaster and depression nexus. Our findings suggest the need to provide commitment devices to mitigate harmful outcomes induced by aggravated hyperbolic discounting resulting from disaster exposure. Hence, we believe that our study sheds new light on post-disaster rehabilitation policies.

The rest of the paper is organized as follows. Section II lays out our research strategy to empirically examine the impact of disaster damage on the present bias of affected residents. Section III discusses the data from Iwanuma and Futaba and presents the empirical results. Finally, Section IV contains concluding remarks on our findings.

II. The Empirical Model

We investigate whether exposure to a disaster makes people present biased. To formulate an empirical model, we define treatment variable d, an ordered variable of exposed disaster-damage level. Then, we set up a standard analysis of covariance (ANCOVA) model to estimate the treatment effect:

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during the peak of the Korean War are more risk averse about five decades later. Voors et al. (2012) showed that individuals exposed to temporal violence display more risk-seeking behavior and have higher discount rates in the long term.

[3] To the best of our knowledge, the only exceptions are Sawada and Kuroishi (2015a, 2015b).

(1) $$Y_{it} = \alpha_0 + \delta d_i + \gamma Y_{it\text{-}1} + X_{it}\beta + \varepsilon_{it},$$

where Y is "present bias" or the hyperbolic discounting level, X is a set of observed control variables, and ε is a well-behaved error term. In Equation 1, the disaster's "treatment" effects can be captured by the estimated parameter, δ, provided that disaster exposure d is orthogonal to the error term. In addition to Equation 1, we also accommodate heterogeneous treatment effects by allowing for treatment effect δ to be specific to the initial level of present bias. The following equation represents this augmented empirical model:

(2) $$Y_{it} = \alpha_0 + \delta d_i + \gamma Y_{it\text{-}1} + \delta^Y d_i \times Y_{it\text{-}1} + X_{it}\beta + \varepsilon_{it},$$

where δ^Y comprises the heterogeneous treatment effects, depending on the initial level of present bias. If $\delta^Y>0$, then disaster exposure aggravates an individual's present bias.

III. Key Variables, Data, and Empirical Results

To estimate equations 1 and 2, we adopt our sui generis dataset from original surveys administered to residents of Iwanuma and Futaba. To measure present bias after the disaster, we use information about the timing of mailing New Year's cards, a unique Japanese custom. According to the Japan Post, the company sold a total of 3.2 billion cards for 2016 (Japan Post 2016), meaning that a Japanese sent around 30 New Year's cards on average. Since New Year's cards are supposed to ideally arrive on January 1st, people need to send them at least two weeks in advance (i.e., on or before December 15th) according to the Japan Post (Japan Post 2017).[4] Presumably, hyperbolic discounters procrastinate at writing and sending cards. Our strategy is to quantify each individual's level of present bias or hyperbolic discounting factor by capturing the timing of when the very first New Year's card is mailed. More specifically, to measure our main variable, Y_t, in equations 1 and 2, we employ each respondent's answer for the following question in our survey, "*When did you mail the first New Year's card for 2016?*" We conduct the survey in 2016 and compute the number of days each respondent took to send the first New Year's card since December 1st, establishing that a higher number of Y_t presents a higher level of present bias or hyperbolic discounting.[5] The distribution of the present bias variable is presented in

[4] If a New Year's card is mailed after December 15th and is clearly marked as that type of card, it will be treated separately from other outgoing mail.

[5] We developed the variable of the level of present bias, setting any date in November as 0, December as its date, and January as its date plus 31. In Japan, people do not usually send New Year's cards if

Table A1 and Table A4 in the Appendix, respectively, for Iwanuma and Futaba.

To measure present bias or hyperbolic discounting before the disaster, Y_{t-1}, we follow Ikeda, Kang, and Ohtake (2010) to capture each individual's timing for completing homework assignments during elementary and junior high school summer vacations. Elementary and junior high school education is compulsory in Japan. Since summer vacation is the longest holiday for students in elementary and high school, lasting around 40 days, most schools provide a substantial amount of homework for students to do during the long vacation. When to complete homework is under each student's self-control, and although it is not a pleasant task in most cases, we believe it is the best measure to capture present bias or hyperbolic discounting during each respondent's adolescence. Specifically, we employed a response to the question, "*When did you work on your summer vacation homework when you were in elementary school?*" for respondents from Iwanuma and "*When did you work on your summer vacation homework when you were in junior high school?*" for participants from Futaba. We asked them to choose from the following five choices: (1) *At the beginning of summer vacation*; (2) *Relatively at the beginning of summer vacation*; (3) *Equally every day*; (4) *Relatively at the end of summer vacation*; and (5) *At the end of summer vacation*. For the analysis, we treat our homework variable as a continuous variable where the higher the value, the greater the level of present bias. The distribution of this variable of present bias, in relation to when the participants were in elementary or junior high school, is presented in Table A2 and Table A5 in the Appendix for Iwanuma and Futaba, respectively.

As for damage level, *d*, we adopt home damage level, which we asked about in our questionnaire. Note that the government officially certified each home damage level through carefully designed metrical surveys. Hence, we believe that these damage level data are accurate. For the survey in Iwanuma, we have the following answer choices: (1) *No significant damage*; (2) *Partially damaged*; (3) *Half destroyed*; (4) *Nearly collapsed*; and (5) *Totally collapsed*. For the survey in Futaba, we decided, along with the Futaba town office, to merge the disaster damage category of "*Nearly collapsed*" with "*Half destroyed*," following the damage level categories used for official reports on the Great East Japan Earthquake by the Fire and Disaster Management Agency of Japan's Ministry of Internal Affairs and Communications. This led to the development of four answer choices: (1) *No significant damage*; (2) *Partially damaged*; (3) *Half destroyed*; and (4) *Totally collapsed*. We treat each damage variable as a

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they are in mourning. We excluded those who said they did not send out cards because they were grieving. This treatment would be justifiable because mourning can be considered exogenous. We also excluded those who did not mention when they mailed New Year's cards. As for the data from Iwanuma, 11.3% of respondents (748 out of 6,647) were in mourning, and 18.7% (1,240 out of 6,647) did not send New Year's cards. As for the data from Futaba, 11.4% of respondents (57 out of 499) were in mourning and 14.0% (70 out of 499) did not send New Year's cards.

continuous one.[6] Tables A3 and A6 in the Appendix show the descriptive statistics of these variables for Iwanuma and Futaba, respectively.

Furthermore, in order to measure the respondents' state of mental health, we included the Kessler Psychological Distress Scale ($K6$) questions based on Kessler et al. (2002).[7] The $K6$ score is known as a clinically-validated depression measure. For each question in the $K6$ battery, the respondents selected an answer on a scale from 0 to 4. The total score for the six questions is summarized as the respondent's $K6$ score; higher scores indicate a greater propensity for mental health problems.

Finally, in order to control the effect arising from observed heterogeneous characteristics, we employ a set of the following control variables, X, in equations 1 and 2: the total number of 2016 New Year's card mailed (*Number of New Year's cards mailed*), as well as each respondent's age and sex.

A. The Case of Iwanuma

Iwanuma, a coastal municipality located in Miyagi Prefecture in Japan, is approximately 80 km west of the epicenter of the Great East Japan Earthquake, which seriously affected the city. A total of 187 residents lost their lives or were declared missing, 5,542 housing units were destroyed, and 48% of the land was inundated by the tsunami (Miyagi Prefecture 2016).[8]

The Iwanuma dataset was collected as part of the Japan Gerontological Evaluation Study (Tsuboya et al. 2016; Hikichi et al. 2016; Hikichi et al. 2017). Using the city's basic resident registration system, we administered a questionnaire survey by post to all Iwanuma residents aged 65 years or older in November 2016 (n=7,421). The response rate was 74.5%. We obtained the information on home damage from the November 2013 survey data.[9]

To check the randomness of the treatment, d, we perform a baseline balancing test by regressing the pre-disaster present bias variable (Y_{t-1}) on the level of home damage caused by the disaster. Table 2 contains the results of the baseline balancing test. In this table, we can verify that there is no systematic relationship between the level of home damage and baseline present bias, suggesting that the treatment (i.e., exposure to disaster damage) is randomly assigned.

In Table 3, columns 1 and 2 present the estimation results of the standard ANCOVA model of Equation 1, while and columns 3 and 4 display the results of estimating Equation 2, with the interaction

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[6] We excluded those who did not answer the question about damage level from our analysis.

[7] The questionnaires adopted in the two studies are available upon request from the corresponding author.

[8] Iwanuma had around 44,187 residents in 15,519 households before the disaster in 2010, which increased slightly to 44,678 residents and 16,631 households as of 2015 (Census 2010 and 2015).

[9] Men 34.0% (n=1,177), women 43.2% (n=1,499), and unknown gender 22.8% (n=790).

term of d (damage) and $Y_{t\text{-}1}$ using Iwanuma data. We show robust standard errors in parenthesis clustered by settled areas before the disaster. As for the control variables, columns 1 and 3 include controls for age and gender, while columns 2 and 4 contain additional controls for the total number of New Year's cards that each respondent mailed.[10]

While the home damage coefficients are all negative for Iwanuma in Table 3, $Y_{t\text{-}1}$ shows significantly positive coefficients (columns 1 and 2), indicating the persistence of present bias. The interaction terms between the treatment effect of damage (d) and pre-disaster present bias ($Y_{t\text{-}1}$) display the following positive coefficients: 0.313 ($p<0.10$) with age and gender controls in column 3; and 0.317 ($p<0.05$), additionally controlled for the number of New Year's cards in column 4. These results suggest that exposure to a disaster aggravates an individual's present bias, captured in elementary school.

We checked the robustness of our findings in two ways. First, we adopt an alternative specification: Considering that New Year's cards should be mailed by December 25th for a timely arrival on New Year's Day (Japan Post, 2017), we estimate equations 1 and 2 using Y_t, captured by a binary variable, which takes 1 if mailed after the cut-off of December 25th, and 0 if otherwise. The conclusions of the cross term of d and $Y_{t\text{-}1}$ are largely consistent with using the continuous variable (Tables A4, A5).

Second, to validate the use of the day when New Year's cards were mailed as a proxy for present bias, we examined the correlation between this variable and present bias measured by the Convex Time Budget (CTB) experiments developed by Andreoni and Sprenger (2012). The latter experimental data set is collected by incentivized artifactual field experiments, carried out in Iwanuma from February to May of 2017, with a subset of the respondents taken from the Iwanuma census data used in this study (Kuroishi and Sawada, 2018).[11] Figure 1 shows the relationship between the day when New Year's cards were mailed on the horizontal axis, and the hyperbolic discount factor, elicited by the CTB experiments, on the vertical axis. We can see a negative relationship between these two variables, with a linear simple regression coefficient of -0.00827 ($P < 0.1$), thus validating the variable of the day when New Year's cards were mailed as a proxy measure of hyperbolic discounting (Table

[10] It should be noted that we included the missing values of a number of New Year's cards in the analysis, but Table 3 does not display them. These outcomes are not reported, but are available from the corresponding author upon request.

[11] For the methodology, see Ashida, Sawada, and Kuroishi (2016) and Sawada and Kuroishi (2015b). We selected the subjects from a sample of individuals aged 65 years or older who are cognitively and physically independent (that is, not certified as needing long-term care service). A total of 179 residents participated in our field experiments on February 8th (26 participants), 9th (11 participants), 10th (21 participants), 11th (16 participants), 14th (15 participants), 21st (26 participants), 27th (29 participants), and 28th (24 participants), as well as March 28th (6 participants) and 29th (5 participants) in 2017 (Sawada and Kuroishi 2018).

A6).

B. The Case of Futaba

Futaba is a town in Fukushima Prefecture, located within 2 to 10 km of Fukushima Daiichi Nuclear Power Plant, where the nuclear accident occurred following the Great East Japan Earthquake. Futaba experienced 167 direct and indirect deaths caused by the disaster (Fukushima Prefecture 2017). While the tsunami and earthquake seriously damaged some areas of Futaba, the nuclear fallout had the biggest impact. Since most areas in Futaba remain under a government-mandated evacuation order, residents are forbidden from returning to their homes. Therefore, Futaba residents have continued to be evacuated to other parts of Japan for more than 7 years. Iwasaki, Sawada, and Aldrich (2017) report unusually high level of stress among Futaba residents following the long evacuation period.

With the support of the Futaba town office, we sent survey questionnaires to around 3,000 addresses listed as regular recipients of the town newsletter in July 2016.[12] Due to practical constraints, we only addressed our survey forms to household heads. We received 499 replies; the response rate is around 17%.[13] Table 1 depicts summary statistics of all the variables used for the analysis. In addition, we explain the distribution of the main variables in the methods section. They are Y_t, the present bias level after the disaster; $Y_{t\text{-}1}$, the present bias level before the disaster when the respondents were in junior high school; and d, the damage level. The Appendix shows descriptive statistics of these variables in Tables A7, A8, and A9, respectively.

Since random assignments of damage exposure are critical presumptions for our identification strategy to be valid, we perform a baseline balancing test by regressing the baseline present bias level, $Y_{t\text{-}1}$, on damage level, represented by d. Table 2 displays the results of the baseline balancing test, which shows no statistically significant relationship between damage level and the baseline present bias level. This result confirms the validity of our randomization assumption.

In the Futaba survey with 499 observations, we can only use 274 due to missing data in the two key variables: Y_t (the day when New Year's cards were mailed) and d (damage). Columns 5 and 6 of Table 3 show the estimation results of the canonical ANCOVA model of Equation 1, while columns 7 and 8 of Table 3 portray the estimation results of Equation 2, which includes the interaction terms of

[12] According to the Population Census of 2010 and 2015, Futaba had around 6,900 residents and 2,600 households before the disaster in 2010, and about 6,600 residents and 2,300 households as of 2015.

[13] This response rate is not necessarily low if we consider general response rates for surveys in Japan. Moreover, the actual response rate would be higher than 17% because the 3,000 addresses include duplications of both registered addresses of household heads and those who requested the newsletter.

$Y_{t\text{-}1}$ and *d,* with different controls for the Futaba data. Wild cluster bootstrap standard errors are presented in parenthesis (clustered by 20 settled areas before the disaster in Futaba). Columns 5 and 7 include controls for age and sex, while columns 6 and 8 include additional controls for the total number of New Year's cards that each respondent mailed.[14]

As for the estimation results of Equation 1 in columns 5 and 6 of Table 3, while the estimated coefficients on *d* (damage) are positive, they are statistically insignificant. Taking into account the heterogeneous impact of the disaster based on pre-disaster present bias, the estimation results of Equation 2 in columns 7 and 8 show that the interaction terms, $d \times Y_{t\text{-}1}$, are positive and statistically significant, indicating that exposure to disaster damage aggravates pre-disaster present bias in junior high school. The coefficients on $Y_{t\text{-}1}$ are positive in specifications 5 and 6, indicating a permanent effect of present bias, but are only marginally significant with *p*-values 0.125 and 0.24, respectively.

To check the robustness, we estimate the models of equations 1 and 2 using the binary dependent variable, as done before (Table A13), confirming the validity of the qualitative results shown in Table 3. Moreover, since some Futaba residents still live in temporary units – unlike Iwanuma residents (Table A10) – the temporal nature of housing may influence residents' behavior in terms of mailing New Year's cards.[15] To consider this potential effect, we estimate equations 1 and 2, including housing type dummies, as additional control variables. The estimation results are not qualitatively different from the results displayed in Table 3, revealing that the cross term of *d* and $Y_{t\text{-}1}$ shows significance (Table A8).

Overall, the qualitative results of the heterogeneous disaster effects on present bias from the Futaba data are the same as those from the Iwanuma data. However, the *magnitude* of the coefficients on the interaction term of *d* and $Y_{t\text{-}1}$ is consistently larger for Futaba than for Iwanuma. This may reflect differentiated exposure to disasters: While residents of Iwanuma were only exposed to the tsunami, Futaba residents were affected by *both* the tsunami and displacement due to the nuclear power plant failure.

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[14] The dummy variables for missing data of $Y_{t\text{-}1}$ and *Number of New Year's cards mailed* are included for analysis, but omitted from the table. These coefficients are not reported in the table, but are available from the corresponding author upon request. The dummies for missing data, the missing observations of $Y_{t\text{-}1}$ and *Number of New Year's cards mailed*, are replaced by zeroes. To check the robustness of our missing value treatments, we also conduct an analysis treating missing data by list-wise deletion. Qualitatively speaking, we obtain the same results. These outcomes are not reported, but are available from the corresponding author upon request.

[15] Those who live in temporary units might be unwilling to send New Year's cards to others from their temporary address.

C. Mental Health Outcomes

Existing studies document that exposure to disasters can cause mental distress (Van Griensven et al.; 2006; Kumar et al. 2007; Frankenberg et al. 2008; Fergusson et al. 2014; Tsuboya et al. 2016; Iwasaki, Sawada, and Aldrich 2017). In order to examine the causal relationship between disaster exposure to present bias as a key mechanism behind the disaster and mental health nexus, we run a regression model of mental distress, adopting a clinically-validated depression measure, with $K6$ as an outcome variable.

There are two specific empirical models. First, we estimate a reduced-form model by regressing the $K6$ measure on the home damage variable, d. As seen in Table 4, the coefficients on damage are positive and statistically significant in specifications 1 and 3 in Table 4, respectively, using the Iwanuma and Futaba data, thus indicating the causal relationship between disaster exposure and mental distress. The point estimate is around four times higher for Futaba than that of Iwanuma; this is consistent with the findings of Iwasaki, Sawada, and Aldrich (2017), who showed the level of stress to be unusually high in Futaba compared with people across Japan, and with those affected by the earthquake and/or tsunami, but not the nuclear catastrophe.

Second, we postulate a structural model where depression is driven by the current present bias, Y_t, which is determined by Equation 2. In this case, we can adopt a standard instrumental variable regression model to estimate a structural parameter, representing the impact of change in present bias Y_t on mental health outcomes, captured by $K6$. The estimation results of the second-stage equation are shown in specifications 2 and 4 of Table 4 for Iwanuma and Futaba, respectively. Both coefficients are positive and fairly significant. The over-identification test results also support the validity of our model. These findings imply that one of the channels of the causal relationship between disaster exposure and depression can be reinforced hyperbolic discounting through exposure to a natural hazard triggered disaster.[16]

[16] To check the robustness, we estimate the model, including housing type dummies, as additional controls for Futaba (Table A12), and we use the binary variable for the day when New Year's cards were mailed as the dependent variable (Table A 15 and Table A14). The qualitative results are robust against these specification changes.

IV. Concluding Remarks

To provide a new insight into the impact of disasters, we investigate the nexus between the damage they cause and individuals' present bias. We adopt sui generis data collected from two communities that were seriously affected by the Great East Japan Earthquake: Iwanuma and Futaba. In both places, we found that exposure to disasters aggravates an individual's present bias. Moreover, the *magnitude* of the effect is consistently larger for Futaba than for Iwanuma. This highlights the seriousness of "compound" disasters: Residents of Iwanuma were only exposed to a tsunami, but Futaba's residents were affected by both the tsunami and displacement due to the nuclear power plant failure. Furthermore, this causal relationship is a key mechanism behind the disaster and depression nexus: As a byproduct, we also find that mental stress, captured by $K6$, is possibly associated with post-disaster present bias. In other words, those who experience greater distress tend to express more procrastination behaviors. Our results suggest the need to provide commitment devices in order to mitigate harmful outcomes induced by disaster exposure. Hence, our study sheds new light on disaster rehabilitation policies. Further investigations on the mechanisms underlying disaster damage, mental health, and present bias in different post-disaster situations will be critical for the further external validation of our results.

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Table 1: Summary of Descriptive Statistics of Iwanuma and Futaba Data

Variable	Iwanuma					Futaba				
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Y_t (Day when New Year's cards were mailed)	1,198	22.73	6.81	1	57	295	23.17	7.43	0	46
Y_{t-1} (Homework)	2,255	3.15	1.23	1	5	449	3.14	1.29	1	5
d (Damage)	3,466	1.88	1.02	1	5	469	1.99	0.90	1	4
$K6$	2,330	4.35	4.33	0	24	442	8.38	6.28	0	24
Number of New Year's cards mailed	1,810	51.16	57.91	1	830	445	28.30	39.72	0	300
Age	2,600	79.21	5.77	65	102	476	66.86	13.27	31	93
Dummy=1 if female	3,466	0.43	0.50	0	1	499	0.21	0.41	0	1
Dummy=1 if no answer for sex	3,466	0.23	0.42	0	1	499	0.03	0.18	0	1

Notes: Y_t represents the level of present bias after the disaster, measured by the date on which the respondents mailed their first New Year's card of 2016. Higher numbers indicate more present bias. Y_{t-1} is the pre-disaster level of present bias when the participants were in junior high school, measured by when they did their summer vacation homework. Higher numbers signal more present bias. d is the level of home damage caused by the disaster. A five-point scale was used for the Iwanuma data and a four-point scale was used for the Futaba data. Higher numbers represent more serious damage. $K6$ gauges mental health. Higher numbers suggest more serious stress. *Number of New Year's cards mailed* is the total number of New Year's cards for 2016 that each respondent mailed.

Table 2: Baseline Balancing Test

	(1)	(2)	(3)	(4)
Data	Iwanuma	Iwanuma	Futaba	Futaba
Dummy=1 if there was no significant home damage	Reference	Reference	Reference	Reference
Dummy=1 if the disaster caused partial home damage	0.0633	0.0633	0.0828	0.0828
	(0.0557)	(0.0535)	(0.143)	(0.0563)
Dummy=1 if the disaster destroyed half of the home	0.0372	0.0372	-0.0678	-0.0678
	(0.106)	(0.116)	(0.183)	(0.124)
Dummy=1 if the disaster nearly caused the home to collapse	-0.149	-0.149	-	-
	(0.151)	(0.184)		
Dummy=1 if the disaster destroyed the home	0.0970	0.0970	-0.242	-0.242
	(0.152)	(0.161)	(0.258)	(0.307)
Constant	3.121***	3.121***	3.142***	3.142***
	(0.0410)	(0.0389)	(0.108)	(0.0713)
N	2,255	2,255	437	437
Adjusted R-squared	-0.000	-0.000	-0.002	-0.002

Notes: Dependent variable Y_{t-1} (homework) regressed on the dummies of d (damage).

Robust standard errors for columns 1 and 3, as well as cluster robust standard errors (clustered by 100 settled areas before the disaster in Iwanuma, and 21 settled areas before the disaster in Futaba) for columns 2 and 4, are in parentheses.

* Significant at the 10% level ** Significant at the 5% level *** Significant at the 1% level

Table 3: Estimation Results of Equations 1 and 2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Data	Iwanuma	Iwanuma	Iwanuma	Iwanuma	Futaba	Futaba	Futaba	Futaba
d (Damage)	-0.0636	-0.102	-1.054*	-1.105*	0.599	0.593	-1.691	-1.807
	(0.206)	(0.208)	(0.594)	(0.600)	(0.783)	(0.776)	(1.390)	(1.567)
Y_{t-1} (Homework)	0.493***	0.473***	-0.0793	-0.106	0.495	0.368	-1.004	-1.239
	(0.175)	(0.171)	(0.317)	(0.317)	(0.322)	(0.313)	(0.799)	(0.869)
$d \times Y_{t-1}$			0.313*	0.317**			0.776**	0.827**
			(0.158)	(0.159)			(0.299)	(0.367)
Number of New Year's cards mailed		-0.00648**		-0.00646**		-0.0183*		-0.0199*
		(0.00295)		(0.00292)		(0.0102)		(0.0113)
Age	-0.0274	-0.0292	-0.0281	-0.0299	-0.147***	-0.146***	-0.151***	-0.149***
	(0.0394)	(0.0396)	(0.0390)	(0.0392)	(0.0521)	(0.0514)	(0.0534)	(0.0527)
Dummy=1 if male	Reference	Reference	Reference	Reference	Reference	Reference	Reference	Reference
Dummy=1 if female	1.956***	1.713***	1.944***	1.701***	-0.257	-0.461	-0.337	-0.537
	(0.332)	(0.379)	(0.331)	(0.378)	(1.069)	(0.956)	(1.126)	(1.067)
Dummy=1 if no answer for sex	-7.521***	-6.561***	-8.380***	-7.434**	-1.796	-1.655	-1.913	-1.767
	(1.347)	(2.116)	(2.069)	(2.835)	(2.400)	(2.394)	(2.557)	(2.556)
N	1,056	1,056	1,056	1,056	274	274	274	274
Adjusted R-squared	0.024	0.027	0.026	0.029	0.073	0.078	0.080	0.087

Notes: The dependent variable is Y_t (the day when New Year's cards were mailed). Columns 1 to 4 present results using the Iwanuma data, and columns 5 to 8 display outcomes using the Futaba data. Columns 1, 2, 5 and 6 depict the estimation results of Equation 1, and columns 3, 4, 7 and 8 show the estimation results of Equation 2. Cluster robust standard errors (clustered by 100 settled areas before the disaster in Iwanuma) are in parentheses for columns 1 to 4. Wild cluster bootstrap standard errors (clustered by 20 settled areas before the disaster in Futaba) are in parentheses for columns 5 to 8. The constant term is not presented. Other omitted control variables include dummy variables for missing data of Y_{t-1} for all columns; a dummy variable for missing data of *Number of New Year's cards mailed* in columns 2, 4, 6 and 8; and a cross term of *d* and the dummy variable for missing data of Y_{t-1} for columns 3, 4, 7 and 8. Those coefficients are not reported in the table, but are available from the corresponding author upon request. Since we include the dummies for missing data, Y_{t-1} and *Number of New Year's cards mailed* include missing data, replaced by 0.

* Significant at the 10% level ** Significant at the 5% level *** Significant at the 1% level

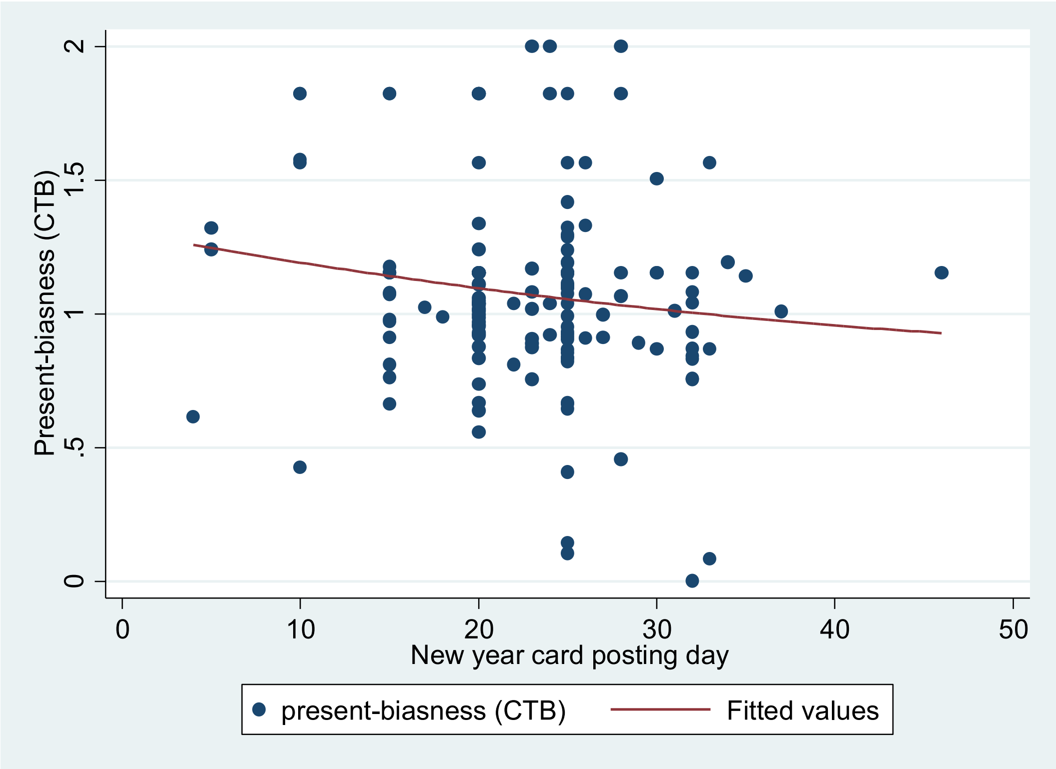
Table 4: Estimation Results of Regressing *K*6 on *d* (Damage) and Instrumented Y_t

	(1)	(2)	(3)	(4)
Data	Iwanuma	Iwanuma	Futaba	Futaba
Method	OLS	IV	OLS	IV
d (Damage)	0.296***		1.112**	
	(0.0878)		(0.494)	
Y_t (Day when New Year's cards were mailed): Instrumented		0.433**		0.321+
		(0.179)		(0.222)
Age	0.126***	0.132***	0.0644	0.114**
	(0.0143)	(0.0313)	(0.0548)	(0.0581)
Dummy=1 if male	Reference	Reference	Reference	Reference
Dummy=1 if female	0.762***	-0.272	0.983	-0.0414
	(0.186)	(0.368)	(1.800)	(0.568)
Dummy=1 if no answer for sex	0.825	2.960	-1.769	-0.758
	(2.039)	(2.453)	(1.211)	(1.011)
Constant	-6.565***	-16.16***	1.743	-7.209
	(1.072)	(5.037)	(3.462)	(8.045)
N	2,230	975	424	254
Adjusted R-squared	0.038	-0.421	0.046	-0.028
Over identification test (p-value)		3.911 (0.1415)		6.063 (0.416)

Notes: The dependent variable is *K*6. Columns 1 and 2 show outcomes using the Iwanuma data, while columns 3 and 4 display results using the Futaba data. Cluster robust standard errors are in parentheses for columns 1 and 2 (clustered by settled areas before the disaster in Iwanuma). Wild cluster bootstrap standard errors in are column 3 (clustered by 21 settled areas before the disaster in Futaba). Cluster bootstrap standard errors are in column 4 (clustered by 18 settled areas before the disaster in Futaba). Columns 2 and 4 present the second stage estimation results of two-stage least squares regression. Here, Y_t is instrumented by *d* (damage), Y_{t-1}, $d \times Y_{t-1}$, a dummy variable for missing data of Y_{t-1}, and a cross term of d and the dummy variable for missing data of Y_{t-1}, *Number of New Year's cards mailed*, a dummy variable for missing data of *Number of New Year's cards mailed*, age and sex dummies. Since we include the dummy for missing data, Y_{t-1} includes missing data, replaced by 0.

+Significant at the 15% level * Significant at the 10% level ** Significant at the 5% level *** Significant at the 1% level

Fig. 1: Relationship Between Present Bias Captured by Quasi-hyperbolic Discounting Factor, Based on the Convex Time Budget Experiments and the Timing of Mailing New Year's Cards



Horizontal axis: The day when New Year's cards were mailed for the first time.

Vertical axis: The level of present bias captured by the Convex Time Budget (CTB) experimental data.

We excluded a respondent who answered more than 60 days (N=1) after our analysis.

Appendix

1. Iwanuma Data

Table A1. Iwanuma Distribution of Present Bias after the Disaster
(The day when New Year's cards for 2016 were mailed)

Month	Date	Freq	Percent	Month	Date	Freq	Percent
December	1	7	0.58	January	1	29	2.42
	2	1	0.08		2	27	2.25
	4	2	0.17		3	25	2.09
	5	6	0.50		4	5	0.42
	10	64	5.34		5	9	0.75
	12	1	0.08		6	1	0.08
	13	1	0.08		7	2	0.17
	14	1	0.08		10	6	0.50
	15	96	8.01		15	1	0.08
	16	1	0.08		20	6	0.50
	18	5	0.42		23	1	0.08
	20	396	33.06		25	2	0.17
	21	5	0.42		26	1	0.08
	22	4	0.33				
	23	22	1.84				
	24	24	2.00				
	25	298	24.87				
	26	16	1.34				
	27	29	2.42				
	28	52	4.34				
	29	11	0.92				
	30	37	3.09				
	31	4	0.33	Total		1,198	100

Table A2: Iwanuma Distribution of Pre-disaster Level of Present Bias when Respondents Were in Elementary School (Answer to the Question: *When did you work on your summer vacation homework when you were in elementary school?*)

	Freq	Percent
1. At the beginning of summer vacation	202	8.32
2. Relatively at the beginning of summer vacation	616	25.37
3. Equally every day	406	16.72
4. Relatively at the end of summer vacation	699	28.79
5. At the end of summer vacation	332	13.67
I did not do it.	45	1.85
I did not have it.	128	5.27
Total	2,428	100

Note: We excluded those who responded, “I did not do it” or “I did not have it.”

Table A3: Iwanuma Distribution by Home Damage Level

	Freq	Percent
1. No significant damage	1,423	41.06
2. Partially damaged	1,496	43.16
3. Half destroyed	257	7.41
4. Nearly collapsed	131	3.78
5. Totally collapsed	159	4.59
Total	3,466	100

Table A4: Iwanuma: Estimation Results of Equations 1 and 2

(Dependent Variable: The day when New Year's cards were mailed)

	(1)	(2)	(3)	(4)
d (Damage)	0.00364	0.00142	-0.0633*	-0.0657*
	(0.0128)	(0.0130)	(0.0355)	(0.0357)
$Y_{t\text{-}1}$ (Homework)	0.0179+	0.0170+	-0.0207	-0.0218
	(0.0109)	(0.0108)	(0.0232)	(0.0232)
$d \times Y_{t\text{-}1}$			0.0212*	0.0212*
			(0.0112)	(0.0113)
Number of New Year's cards mailed		-0.000423**		-0.000421**
		(0.000197)		(0.000194)
Age	0.00105	0.000977	0.00100	0.000927
	(0.00252)	(0.00251)	(0.00250)	(0.00249)
Dummy=1 if male	Reference	Reference	Reference	Reference
Dummy=1 if female	0.127***	0.112***	0.126***	0.111***
	(0.0198)	(0.0219)	(0.0198)	(0.0219)
Dummy=1 if no answer for sex	-0.153***	-0.0905	-0.211**	-0.149
	(0.0447)	(0.0958)	(0.0962)	(0.147)
N	1056	1056	1056	1056
Adjusted R-squared	0.019	0.021	0.021	0.023

Notes: The dependent variable is a dummy variable that takes 1 for those who mailed New Year's cards after December 25th. Columns 1 and 2 present the estimation results of Equation 1, while columns 3 and 4 display the estimation outcomes of Equation 2. Cluster robust standard errors (clustered by 100 settled areas before the disaster in Iwanuma) are in parentheses. The constant term is not presented. Other omitted control variables include dummy variables for missing data of $Y_{t\text{-}1}$ and *Number of New Year's cards mailed*. These coefficients are not reported in the table, but are available from the corresponding author upon request. Since we include the dummies for missing data, $Y_{t\text{-}1}$ and *Number of New Year's cards mailed* include missing data, replaced by 0.

\+ Significant at the 15% level * Significant at the 10% level ** Significant at the 5% level

*** Significant at the 1% level

Table A5: Iwanuma Estimation Results of Regressing *K*6 on Instrumented Binary Y_t

	(1)
Y_t (Dummy for those who mailed New Year's cards after December 25th): Instrumented	5.801+ (3.819)
Age	0.114*** (0.0299)
Dummy=1 if female	-0.239 (0.505)
Dummy=1 if no answer for sex	0.417 (1.794)
Constant	-6.209*** (2.232)
N	975
Adjusted R- squared	-0.226
Over-identification test (p-value)	3.762 (0.1524)

Notes: The dependent variable is *K*6. Robust standard errors are in parenthesis (clustered by 100 settled areas before the disaster in Iwanuma). The column depicts the second stage estimation results of two-stage least squares regression. Here, Y_t is instrumented by d (damage), Y_{t-1}, $d \times Y_{t-1}$, a dummy variable for missing data of Y_{t-1} and a cross term of d, and the dummy variable for missing data of Y_{t-1}, *Number of New Year's cards mailed*, a dummy variable for missing data of *Number of New Year's cards mailed*, age and sex dummies. Since we include the dummy for missing data, Y_{t-1} includes missing data, replaced by 0.

+Significant at the 15% level * Significant at the 10% level ** Significant at the 5% level

*** Significant at the 1% level

Table A6: Iwanuma: Estimation Results of Present Bias by CTB

	(1)
Day when New Year's Cards were mailed	-0.00827*
	(0.00459)
Constant	1.265***
	(0.109)
N	151
Adjusted R-squared	0.015

Notes: The dependent variable is present bias (quasi-hyperbolic discounting), estimated by the CTB method. We obtained this dataset through a survey and field experimental data in Iwanuma in 2017. The subjects were residents 65 years of age and older. We excluded a respondent who answered more than 60 days (N=1) after our analysis.

* Significant at the 10% level ** Significant at the 5% level *** Significant at the 1% level

2. Futaba Data

Table A7. Futaba Distribution of Present Bias After the Disaster
(The day when the first New Year's cards for 2016 were mailed)

Month	Date	Freq	Percent	Month	Date	Freq	Percent
November		3	1.02	January	1	11	3.73
December	1	3	1.02		2	9	3.05
	5	2	0.68		3	7	2.37
	10	20	6.78		4	4	1.36
	15	16	5.42		5	4	1.36
	16	2	0.68		10	3	1.02
	20	78	26.44		15	1	0.34
	21	2	0.68				
	23	5	1.69				
	24	9	3.05				
	25	68	23.05				
	26	4	1.36				
	27	4	1.36				
	28	16	5.42				
	29	2	0.68				
	30	22	7.46	Total		295	100

Table A8: Futaba Distribution of Pre-disaster Level of Present Bias when the Respondents Were in Junior High School (Answer to the Question, *When did you work on your summer vacation homework when you were in junior high school?*)

	Freq	Percent
1. At the beginning of summer vacation	58	11.62
2. Relatively at the beginning of summer vacation	107	21.44
3. Equally every day	60	12.02
4. Relatively at the end of summer vacation	160	32.06
5. At the end of summer vacation	64	12.83
No answer	50	10.02
Total	499	100

Table A9: Futaba Distribution by Home Damage Level

	Freq	Percent
1. No significant damage	157	31.46
2. Partially damaged	192	38.48
3. Half destroyed	86	17.23
4. Totally collapsed	34	6.81
No answer	30	6.01
Total	499	100

Table A10: Futaba Distribution by Housing Type

	Freq	Percent
Temporary unit	27	5.41
Rental unit	105	21.04
Public restoration unit	26	5.21
Owned house	265	53.11
Other kind of unit	51	10.22
No answer	25	5.01
Total	499	100

Table A11: Futaba Estimation Results of Equations 1 and 2 with Housing Type Dummies

	(1)	(2)	(3)	(4)
d (Damage)	0.596	0.606	-1.762	-1.804
	(0.833)	(0.847)	(1.418)	(1.499)
$Y_{t\text{-}1}$ (Homework)	0.463	0.353	-1.067	-1.236
	(0.297)	(0.281)	(0.712)	(0.782)
$d \times Y_{t\text{-}1}$			0.796***	0.824**
			(7.67e-20)	(0.337)
Number of New Year's cards mailed		-0.0157		-0.0167
		(0.0101)		(0.0116)
Age	-0.142***	-0.141***	-0.145***	-0.144***
	(0.0501)	(0.0498)	(0.0513)	(0.0510)
Dummy=1 if male	Reference	Reference	Reference	Reference
Dummy=1 if female	-0.685	-0.752	-0.804	-0.862
	(1.305)	(1.305)	(1.451)	(1.476)
Dummy=1 if no answer for sex	-1.273	-1.287	-1.331	-1.344
	(1.759)	(1.862)	(1.799)	(1.944)
Dummy=1 if living in temporary unit	Reference	Reference	Reference	Reference
Dummy=1 if living in rental unit	2.708	2.734	2.098	2.120
	(3.213)	(3.385)	(3.071)	(3.251)
Dummy=1 if living in public restoration unit	1.555	1.651	0.904	1.005
	(10.29)	(10.49)	(14.39)	(13.34)
Dummy=1 if living in owned house	1.140	1.525	0.438	0.840
	(2.673)	(2.680)	(2.396)	(2.872)
Dummy=1 if living in other kind of unit	3.315	3.314	2.780	2.808
	(3.126)	(3.361)	(3.031)	(3.296)
Dummy=1 if no answer for housing unit	0.482	0.471	0.124	0.333
	(7.685)	(6.821)	(1.304e+19)	(10.62)
N	274	274	274	274
Adjusted R-squared	0.070	0.071	0.078	0.080

Notes: The dependent variable is Y_t (the day when New Year's cards were mailed). Columns 1 and 2 present the estimation results of Equation 1, while and columns 3 and 4 portray the estimation outcomes of Equation 2. Wild cluster bootstrap standard errors (clustered by 20 settled areas before the disaster in Futaba) are in parentheses. The constant term is not presented. Other omitted control variables include dummy variables for missing data of Y_{t-1} in all columns, a dummy variable for missing data of *Number of New Year's cards mailed* in columns 2 and 4, and a cross term of *d* and the dummy variable for missing data of Y_{t-1} for columns 3 and 4. Those coefficients are not reported in the table, but are available from the corresponding author upon request. Since we include the dummies for missing data, Y_{t-1} and *Number of New Year's cards mailed* include missing data, replaced by 0.

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level

Table A12: Futaba Estimation Results of Regressing $K6$ on d (Damage) and Instrumented Y_t with Housing Type Dummies

	(1)	(2)
d (Damage)	0.993*	
	(0.537)	
Y_t (Day when New Year's cards were mailed): Instrumented		0.345+
		(0.224)
Age	0.0667	0.116**
	(0.0457)	(0.0566)
Dummy=1 if male	Reference	Reference
Dummy=1 if female	0.668	-0.287
	(1.493)	(0.706)
Dummy=1 if no answer for sex	-1.275	-0.670
	(0.961)	(0.990)
Dummy=1 if living in temporary unit	Reference	Reference
Dummy=1 if living in rental unit	-1.424	-2.953
	(1.554)	(3.049)
Dummy=1 if living in public restoration unit	-3.873**	-3.863
	(1.831)	(4.270)
Dummy=1 if living in owned house	-3.467**	-4.014
	(1.340)	(2.781)
Dummy=1 if living in other kind of unit	-4.573***	-5.906*
	(1.620)	(3.220)
Dummy=1 if no answer for housing unit	-3.018	-5.895*
	(3.031)	(3.516)
N	424	254
Adjusted R-squared	0.070	-0.033
Over-identification test (p-value)		5.961(0.43)

Notes: Wild cluster bootstrap standard errors (clustered by 21 settled areas before the disaster in Futaba) are in parentheses for column 1. Cluster bootstrap standard errors (clustered by 18 settled areas before the disaster in Futaba) are in parentheses for column 2. The constant term is not presented. Column 2 displays the second stage estimation results of two-stage least squares regression. Here, Y_t is instrumented by d (damage), Y_{t-1}, d × Y_{t-1}, a dummy variable for missing data of Y_{t-1} and a cross term of d and the dummy variable for missing data of Y_{t-1}, *Number of New Year's cards mailed*, a dummy variable for missing data of *Number of New Year's cards mailed*, age and sex dummies. Since we include the dummy for missing data, Y_{t-1} includes missing data as number of 0, following the dummy variable adjustment strategy.

+ Significant at the 15% level * Significant at the 10% level ** Significant at the 5% level

*** Significant at the 1% level

Table A13: Futaba Estimation Results of Equations 1 and 2 with Binary Dependent Variable

	(1)	(2)	(3)	(4)
d (Damage)	0.0462	0.0457	-0.111**	-0.121**
	(0.0444)	(0.0449)	(0.0507)	(0.0585)
$Y_{t\text{-}1}$ (Homework)	0.0238	0.0125	-0.0775***	-0.0978***
	(0.0315)	(0.0308)	(0.0274)	(0.0345)
$d \times Y_{t\text{-}1}$			0.0523***	0.0568***
			(7.67e-20)	(7.67e-20)
Number of New Year's cards mailed		-0.00163**		-0.00172**
		(0.000666)		(0.000735)
Age	-0.00740***	-0.00726***	-0.00767***	-0.00752***
	(0.00262)	(0.00257)	(0.00271)	(0.00266)
Dummy=1 if male	Reference	Reference	Reference	Reference
Dummy=1 if female	-0.0465	-0.0657	-0.0532	-0.0717
	(0.0768)	(0.0739)	(0.0826)	(0.0798)
Dummy=1 if no answer for sex	-0.354**	-0.341***	-0.362**	-0.349***
	(0.145)	(0.120)	(0.155)	(0.123)
N	274	274	274	274
Adjusted R-squared	0.057	0.078	0.069	0.092

Notes: The dependent variable is a dummy variable, taking 1 for those who mailed New Year's cards after December 25th. Columns 1 and 2 present the estimation results of Equation 1, while columns 3 and 4 display the estimation results of Equation 2. Wild cluster bootstrap standard errors (clustered by 20 settled areas before the disaster in Futaba) are in parentheses. The constant term is not presented. Other omitted control variables include dummy variables for missing data of $Y_{t\text{-}1}$ in all columns, a dummy variable for missing data of *Number of New Year's cards mailed* in columns 2 and 4, and a cross term of *d* and the dummy variable for missing data of $Y_{t\text{-}1}$ for columns 3 and 4. These coefficients are not reported in the table, but are available from the corresponding author upon request. Since we include these dummies for missing data, $Y_{t\text{-}1}$ and *Number of New Year's cards mailed* include missing data, represented by 0, following the dummy variable adjustment strategy.

* Significant at the 10% level ** Significant at the 5% level *** Significant at the 1% level

Table A14: Futaba Estimation Results of Regressing *K*6 on Instrumented Binary Y_t

	(1)
Y_t (Dummy for those who mailed New Year's cards after December 25th): Instrumented	5.148+
	(3.159)
Age	0.105*
	(0.0551)
Dummy=1 if male	Reference
Dummy=1 if female	0.174
	(0.630)
Dummy=1 if no answer for sex	0.536
	(1.392)
Constant	-0.730
	(4.578)
N	254
Adjusted R-squared	-0.027
Over-identification test (p-value)	4.585 (0.5981)

Notes: The dependent variable is *K*6. Cluster bootstrap standard errors are in parenthesis (clustered by 18 settled areas before the disaster in Futaba). The column presents the second stage estimation results of two-stage least squares regression. Here, Y_t is instrumented by d (damage), $Y_{t\text{-}1}$, $d \times Y_{t\text{-}1}$, a dummy variable for missing data of $Y_{t\text{-}1}$ and a cross term of d and the dummy variable for missing data of $Y_{t\text{-}1}$, *Number of New Year's cards mailed*, a dummy variable for missing data of *Number of New Year's cards mailed*, age and sex dummies. Since we include the dummy for missing data, $Y_{t\text{-}1}$ includes missing data, replaced by 0.

+Significant at the 15% level * Significant at the 10% level ** Significant at the 5% level *** Significant at the 1% level