Disasters, Present Bias, and Depression:
Evidence from the Great East Japan Earthquake

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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: 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. 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. Using the double difference method, we find 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.

Keywords: disaster; preference; present bias; hyperbolic discounting
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1. Introduction

In this paper, we focus on how disaster damage affects individual present bias, considering the following two issues. First, present bias is closely connected to critical harmful behavior exhibited by victims of natural hazards, manmade disasters, and other traumatic events. In this way, disasters undermine people's livelihoods. Second, the disaster and present bias nexus has rarely been investigated in the literature.[1]

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 adopt the double difference framework and investigate the impact of disaster exposure on the long-term stability of present bias.

2. Key Variables and Data

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 a week in advance (i.e., on or before December 25th) according to the Japan Post (Japan Post 2017). 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, present bias, 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 the variable presents a higher level of present bias or hyperbolic discounting.

To measure present bias or hyperbolic discounting before the disaster, we follow previous studies (Ikeda et al. 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. As we ask respondents' attitude on homework assignment retrospectively, measurement error can be a potential issue. However,

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

even with the possibility of the attenuation bias, we get statistically significant results as we will present in the following sections.

As for damage level, we adopt officially certified 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 while they are self-reported. 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 continuous one.[2]

Furthermore, in order to measure the respondents' state of mental health, we included the Kessler Psychological Distress Scale (*K*6) questions. The *K*6 score is known as a clinically-validated depression measure. For each question in the *K*6 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 *K*6 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: 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.

3. 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 a generalized version of the double difference model, a.k.a, ANCOVA model to estimate the treatment effect:

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

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:

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

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.

Also, 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 *K*6 as an outcome variable. There are two specific empirical models for this analysis. First, we estimate a reduced-form model by regressing the *K*6 measure on the home damage variable, *d*. Second, we postulate

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

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 $K6$.[3]

4. Results and Remarks

First, using the double difference framework or ANCOVA model of equations (1) and (2) applied to our data, we found that exposure to disasters aggravates an individual's present bias, captured in elementary and junior high school in both places (Table 1), which can cause harmful behavior (Ikeda et al. 2010). While this common finding in spite of the differences between Iwanuma and Futaba within the context of disaster exposure can help to verify the external validity of our findings, 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.

Second, we investigate the determinants of mental distress, adopting a clinically-validated depression measure, with $K6$ as an outcome variable. Our empirical results based on the reduced from and structural form of regression are reported in Table 2. These 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 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.

Reference

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[3] For all estimation using Futaba data, we employ Heckman correction method to correct the potential selection bias using 2010 national census data.

Table 1: Double Difference 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*	0.387	0.350	-1.371	-1.498
	(0.206)	(0.208)	(0.594)	(0.600)	(0.686)	(0.680)	(1.220)	(1.414)
Y_{t-1} (Homework)	0.493***	0.473***	-0.0793	-0.106	0.452+	0.312	-0.676	-0.899
	(0.175)	(0.171)	(0.317)	(0.317)	(0.310)	(0.311)	(0.550)	(0.662)
$d \times Y_{t-1}$			0.313*	0.317**			0.585**	0.627**
			(0.158)	(0.159)			(0.232)	(0.272)
Number of New Year's cards mailed		-0.00648**		-0.00646**		-0.0199**		-0.0206*
		(0.00295)		(0.00292)		(0.00949)		(0.0110)
Age	-0.0274	-0.0292	-0.0281	-0.0299	-0.110*	-0.107*	-0.114**	-0.112**
	(0.0394)	(0.0396)	(0.0390)	(0.0392)	(0.0576)	(0.0569)	(0.0536)	(0.0535)
Dummy=1 if male	Reference	Reference	Reference	Reference	Reference	Reference	Reference	Reference
Dummy=1 if female	1.956***	1.713***	1.944***	1.701***	-1.931	-2.107*	-1.969	-2.111+
	(0.332)	(0.379)	(0.331)	(0.378)	(1.421)	(1.269)	(1.453)	(1.321)
Dummy=1 if no answer for sex	-7.521***	-6.561***	-8.380***	-7.434**	0	0	0	0
	(1.347)	(2.116)	(2.069)	(2.835)	(0)	(0)	(0)	(0)
Inverse Mills Ratio	-	-	-	-	2.675*	2.946*	2.520+	2.742*
					(1.596)	(1.679)	(1.562)	(1.648)
N	1,056	1,056	1,056	1,056	6,047	6,047	6,047	6,047
Adjusted R-squared	0.024	0.027	0.026	0.029	0.076	0.081	0.078	0.083

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. Cluster bootstrap standard errors (clustered by 22 settled areas before the disaster in Futaba) are in parentheses for columns 5 to 8. The constant term is not presented. Omitted control variables from column 5 to 8 are house type dummies. 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 2: Estimation Results of Regressing *K*6 on *d* (Damage) and Instrumented Y_t

	(1)	(2)	(3)	(4)	(5)	(6)
Data	Iwanuma	Iwanuma	Iwanuma	Futaba	Futaba	Futaba
Method	OLS	LIML	LIML	OLS	IV	IV
d (Damage)	0.296***			0.819+		
	(0.0878)			(0.564)		
Y_t (Day when New Year's cards were mailed): Instrumented		0.524**	0.499**		0.310*	0.271*
		(0.243)	(0.238)		(0.177)	(0.156)
Age	0.126***	0.133***	0.127**	0.0764**	0.119**	0.101*
	(0.0143)	(0.034)	(0.238)	(0.0301)	(0.0532)	(0.0576)
Dummy=1 if male	Reference	Reference				
Dummy=1 if female	0.762***	-0.419	-0.408	0.359	-0.646	-0.916
	(0.186)	(0.455)	(0.456)	(1.114)	(0.970)	(1.055)
Dummy=1 if no answer for sex	0.825	3.677	4.088	0	0	0
	(2.039)	(2.825)	(2.604)	(0)	(0)	(0)
Inverse Mills Ratio	-	-	-	0.822	1.280	2.040
				(0.909)	(1.447)	(1.570)
Constant	-6.565***	-18.299***	-17.26***	3.607	-5.570	-2.868
	(1.072)	(6.528)	(6.043)	(2.842)	(7.668)	(6.980)
N	2,230	975	975	6047	6047	6047
Adjusted R-squared	0.038	-0.648	-0.576	0.064	-0.014	0.061
Centered R-squared		-0.6409	-0.5594		0.0240	0.1118
Uncentered R-squared		0.1665	0.2080		0.6166	0.6511
Over identification test (p-value)		1.707 (0.4258)	1.633 (0.4419)		5.773 (0.449)	NA
Weak identification test		3.587	3.605		12.249	12.471
(Maximal IV relative bias)		(<25%)	(<25%)		(<10%)	(<10%)

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. Column 3 and 6 include equivalent income variables. Cluster robust standard errors are in parentheses for columns 1 and 2 (clustered by settled areas before the disaster in Iwanuma). Cluster bootstrap standard errors in are 3 to 5 (clustered by 22 settled areas before the disaster in Futaba). Columns 2,3, 5 and 6 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