Chapter 6

How to Strengthen Social Capital in Disaster Affected Communities? The Case of the Great East Japan Earthquake

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CHAPTER 6

How to Strengthen Social Capital in Disaster Affected Communities? The Case of the Great East Japan Earthquake

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In this paper, we investigate two important issues regarding the design and implementation of appropriate disaster management and reconstruction policies. First, we examine the nexus between damage caused by a disaster and preference parameters. Second, we study the impact of individual preference on social capital. With this aim, we employed unique field experiment data collected exclusively for this study from the residents of Iwanuma city, located near Sendai city in Miyagi Prefecture, Japan, who were affected by the March 11th, 2011 earthquake and tsunami. We conducted carefully designed artefactual experiments using the methodology of the Convex Time Budget (CTB) experiments of Andreoni and Sprenger (2012) to elicit present bias, time discount, and risk preference parameters. We also conducted canonical dictator and public goods games to capture the pro-social behaviour, or simply "social capital" of the subjects of the experiments. Four important findings emerged. First, we found an absence of quasi-hyperbolic discounting in the whole sample. Second, we found that disaster damage seems to make individuals more present-biased, although the change observed is not necessarily statistically significant. Third, in dictator games, the amounts sent to victims of the Great East Japan Earthquake were larger than those sent to anonymous persons in Japan. Also, we found that present bias parameter and time discount factor were both negatively related to the amount of donation, implying that seemingly altruistic behaviours might be driven by myopic preference. Finally, we found that present bias is closely related to bonding social capital.

Keywords: Convex Time Budget experiment, Natural Disaster, Risk and Time Preference
JEL Classification: C93,D81,O12.

1. Introduction

On March 11th, 2011, an earthquake measuring 9.0 on the Richter scale off the shore of Japan's northeastern coast in Tohoku caused a tsunami with a maximum height of more than 20 meters (65 feet), which devastated coastal communities. The disaster also shut down the cooling systems and backup generators at the Fukushima Dai-ichi nuclear power plant. The tsunami resulted in the loss of more than 21,500 lives, and the complete destruction of over one-hundred-thousand buildings. While the Great East Japan is admittedly one of the most serious disasters in human history, a variety of disasters hit different parts of the world, too. It has become clear that only a small proportion of damage caused by natural disasters was covered by formal insurance schemes. Can we really protect our livelihoods from catastrophes? What is the role of different market and non-market insurance mechanisms? What lessons can we learn from the aftermath of disasters? This paper tries to provide rigorous evidence to answer some of these questions.

In response to the wide variety of shocks caused by natural disasters, including earthquakes, individuals have developed formal and informal mechanisms to deal with the potential negative consequences. In general, there are two mechanisms: ex-ante risk management and ex-post risk-coping behaviours. Risk management strategies can be defined as the actions of households to mitigate risk and shock before the resolution of uncertainties, including accumulation of precautionary savings, taking out formal disaster insurance such as earthquake insurance, and investment in mitigation such as earthquake-proof housing structures. Even if households adopt a variety of risk management strategies, disasters tend to strike unexpectedly and can have a serious negative impact on household welfare. Therefore, ex-post risk-coping strategies those used to mitigate the downside impacts of shocks to livelihood once a disaster has struck will be needed. Risk coping strategies can take the form of market insurance mechanisms such as receiving insurance payouts, borrowing, and obtaining additional employment; self-insurance mechanisms; and non-market insurance mechanisms provided by government and communities. In theory, idiosyncratic shocks to a household should be absorbed by all other members in the same insurance network and should therefore not affect livelihoods. Market, state, and community mechanisms have the potential to function effectively to minimise the damage caused by disasters. To be able to strengthen these mechanisms, we need to clearly understand the roles of individual and social preferences. To identify effective policies geared towards facilitating livelihood recovery of the victims of a disaster, it is necessary to clarify how individual and social preferences are affected by the disaster.

Individual preference parameters have traditionally been treated as “deep parameters”in economics, i.e., not determined by economic decisions, and therefore constant over time (e.g., Stigler and Becker, 1977). More recently, studies on endogenous formation of individual and social preferences have found that they are not constant over time and that they change under certain circumstances (Fehr and Hoff, 2011). As natural disasters and manmade disasters are traumatic events, they are likely to affect the behaviour of individuals in the short term and possibly the long term. Examples are the studies by Cameron and Shah (2011) and Cassar, *et al.* (2011) on the Indian Ocean tsunami in 2004. Cameron and Shah (2011) found that individuals in Indonesia who suffered a flood or earthquake in the past three years are more risk averse than those who were not affected by a flood or earthquake. Cassar, *et al.* (2011) showed that, after the tsunami in Thailand, individuals affected by the disaster were substantially more trusting, more risk averse and more trustworthy. From these results, they concluded that individual welfare and aggregate growth levels are affected by the change in these social preferences. Callen, *et al.* (2014), investigating the relationship between violence and economic risk preferences in Afghanistan, found a strong preference for certainty and violation of the expected utility framework. Voors, *et al.* (2012) used a series of field experiments in rural Burundi to find that individuals exposed to violence display more altruistic behaviour towards their neighbours and are more risk-seeking: the results indicate that large shocks can have long-term consequences for insurance mechanisms.

In this study, we use the natural experimental situation that emerged in the wake of the March 11th, 2011 earthquake and tsunami disaster in Japan to investigate the nexus between damage caused by the disaster and preference parameters. We also examine how individual preference parameters affect the social capital of disaster-affected people. More specifically, we use unique field experiment data collected from the tsunami-affected residents of

Iwanuma city, located near Senday city in Miyagi Prefecture. We conducted carefully designed artefactual experiments using the methodology of the Convex Time Budget (CTB) experiments of Andreoni and Sprenger (2012) and conducted canonical dictator and public goods games to elicit the extent of individual pro-social behaviour. With the present bias, time discount, and risk preference parameters, as well as the level of social capital identified, we investigated the impact of the damage caused by the earthquake and tsunami.

2. Earthquakes in Japan

Japan is vulnerable to a wide variety of natural disasters such as earthquakes, tsunamis, volcanic eruptions, typhoons, floods, landslides, and avalanches. Of these natural disasters, earthquakes are the most serious and frequently occurring (Sawada, 2013). Japan's continuous earthquake activity is due to the country's location on a subduction zone, where four of the more than 10 tectonic plates covering the globe are crushed against each other. Indeed, of the 912 earthquakes with a magnitude of 6.0 on the Richter scale or greater that occurred worldwide between 1996 and 2005, 190 occurred in or around Japan, meaning that more than 20 percent of the world's large earthquakes took place in or around Japan.

Throughout Japan's history, earthquakes have regularly hit the country: a total of 248 large earthquakes have occurred in Japan in the 1,300 years since the Hakuho earthquakes of 684, the oldest Japanese earthquakes to have been recorded in written form. Moreover, in the Nankai and Tokai areas, large earthquakes occur regularly every 100 to 200 years ("the twin earthquake"). In terms of human losses, the worst earthquake in the country's history was the Great Kanto earthquake of September 1st, 1923, which had a magnitude of 7.9 on the Richter scale. Large parts of Tokyo and Kanagawa were destroyed, several hundred thousand homes and buildings were in ruins, and more than 140,000 people were killed or went missing. The fires that followed the quake spread rapidly as many houses and other buildings were made of wood. In Tokyo, 477,128 houses, or 70 percent of the total, burnt down, with the fire blazing for a full three days. Thus some 44 percent of

Japan's gross domestic product (GDP) in 1922 was lost either directly as a result of the earthquake, or indirectly due to the fires, aftershocks, and tsunamis. Aiming never to forget the lessons of the Great Kanto earthquake, the Japanese government declared September 1st an annual day of earthquake disaster prevention exercises and related activities.

Since this time, through the development of disaster management systems and enhanced disaster information communication systems, the death toll and number of missing persons from disasters, most particularly earthquakes, has declined, with the two notable exceptions of the Great East Japan earthquake in 2011 and the Great Hanshin-Awaji (Kobe) earthquake in 1995. Particularly, we see vividly the 2011 devastating earthquake, tsunami, and nuclear radiation crisis in Japan that has killed tens of thousands people and resulting in damage of around 200 to 300 billion dollars. These two exceptions highlight the significance of natural disasters which can generate the most serious consequences ever known (Sawada, 2013).

The Kobe earthquake struck at 5:46 a.m. on January 17th, 1995, hitting an area that is home to 4 million people and contains one of Japan's main industrial clusters. The earthquake, which registered 7.3 on the Richter scale, cost 6,432 lives excluding 3 missing persons, resulted in 43,792 injured, and damaged 639,686 buildings, of which 104,906 were completely destroyed (Fire and Disaster Management Agency, 2006). Together with Hurricane Katrina, the Kobe earthquake caused the largest economic loss due to a natural disaster in history. The loss in housing property amounted to more than USD 60 billion, while that in capital stock exceeded USD 100 billion (Horwich, 2000).

The Great East Japan Earthquake of March 11th, 2011, itself caused relatively little damage to the residents and buildings in the northeast region of Japan known as Tohoku. However, the massive thrust-fault set off a tsunami with a maximum height of more than 20 meters (65 feet) which devastated coastal communities and shut down the cooling systems and backup generators at the Fukushima Dai-ichi nuclear power plant. The March 11 disaster resulted in the loss of more than 21,500 lives, and the complete destruction of over one hundred thousand buildings.

3. Data

We collected our experimental data in Iwanuma City in Miyagi Prefecture, which is located next to Sendai city and hosts Sendai airport. The city suffered enormous damage from the March 11th 2011 Great East Japan Earthquake, in part because the city faces the ocean and its terrain is quite flat. One-hundred-eighty lives were lost and 2,766 homes either collapsed or were seriously damaged in the city. Of all the areas affected by the tsunami, the proportion of the area submerged by the tsunami wave was the largest in Iwanuma city.

The survey and experimental data we used were collected exclusively for the study. The subjects were selected from the respondents of the Japan Gerontological Evaluation Study (JAGES), a survey conducted in November 2013 among residents aged 65 and over. From the 1,032 residents who agreed to participate in the experiments, we selected 346 respondents who lived in the tsunami affected areas. A total of 187 individuals participated in our field experiments conducted on 15 May (39 participants), 26 May (47 participants), 19 May (29 participants), 20 May (47 participants), and 21 May (25 participants).

4. Parameter Estimation Strategies

To elicit present bias, time discount, and risk aversion parameters, we carefully designed and conducted Convex Time Budget (CTB) experiments as set out in Andreoni and Sprenger (2012) and Andreoni, *et al.* (2013). We employed the data collected by the CTB experiments to separately identify the three key parameters of the utility function: risk aversion parameter, α; time discounting parameter, δ; and present bias parameter, β. As a theoretical framework, we assume a quasi-hyperbolic discounting structure for discounting and the preferences described by:

$$U(x) = u(x_t) + \beta \sum_{k=1}^{\infty} \delta^k u(x_{t+k}) \quad (1)$$

where we postulate a constant relative risk aversion (CRRA) utility, $u(x_{t+k}) = x_{t+k}^{\alpha}$, the parameter δ captures standard long-run exponential discounting, and the parameter β captures a specific preference towards payments in the present, *t* = 0. While present bias is associated with β < 1, β = 1 corresponds to the case of standard exponential discounting.

In the CTB experiment, subjects are given the choice of (*X*, 0), (0, *Y*) or anywhere along the intertemporal budget constraint connecting these points such that $Px_t + x_{t+k} = Y$, where $P = \frac{Y}{X}$ is the gross interest rate. A standard intertemporal Euler equation maintains:

$$MRS = \frac{x_t^{\alpha-1}}{\beta^{\mathbf{1}\{t=t_0\}} \delta^k x_{t+k}^{\alpha-1}} = P \quad (2)$$

where t_0 is an indicator for whether t = 0. This can be rearranged to be linear in these experimental variations, t, k, and P,

$$ln(\frac{x_t}{x_{t+k}}) = \frac{ln(\beta)}{\alpha - 1} t_0 + \frac{ln(\delta)}{\alpha - 1} k + \frac{1}{\alpha - 1} ln(P) \quad (3)$$

Assuming an additive error structure, this is estimable at either the group or individual level. We employ the ordinary least squares (OLS) method to estimate the model given by equation (3).

However, the allocation ratio $ln(\frac{x_t}{x_{t+k}})$ is not well defined at corner solutions. To address this problem, we can use the demand function to generate a non-linear regression equation based on

$$x_t = \frac{10,000(\beta^{t_0} \delta^k P)^{\frac{1}{\alpha-1}}}{1 + P(\beta^{t_0} \delta^k P)^{\frac{1}{\alpha-1}}} \quad (4)$$

which avoids the problem of the logarithmic transformation in (2). We can estimate the model of equation (4) by employing the non-linear least squares (NLS) method.

5 Results

5.1. The Covex Time Budget (CTB) Experiment

Table 6.1 presents the estimation results of aggregated-level homogenous risk aversion parameter, α; time discounting parameter, δ; and present bias parameter, β. The first two columns report the estimated parameter based on equation (4) using NLS and the last column shows results based on equation (3) using OLS. In all specifications, with the estimated present bias parameter and its standard error, we cannot reject the null hypothesis in which the present bias parameter equals one, indicating the absence of quasi-hyperbolic discounting in the whole sample. Moreover, the estimated time discount rate is close to zero and the estimated risk aversion parameter is within a reasonable range. Overall, we can safely say that the subjects from Iwanuma city used in our survey are forward-looking and patient without obvious present bias.

Table 6.1: The Results in Aggregate CTB

	(1) NLS w/o clustering	(2) NLS w/ clustering	(3) OLS
β	1.000***	1.000***	1.009***
	(0.00646)	(0.00674)	(0.0187)
δ	0.999***	0.999***	1.001***
	(0.0000947)	(0.000168)	(0.000597)
α	0.866***	0.868***	0.896***
	(0.00480)	(0.0102)	(0.00612)
N	4474	4450	4450

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Based on the data from the CTB experiments, we can also estimate the individual-level preference parameters. The distributions of all individual preference parameters are shown in Table 6.2. While discount factor and risk parameters are clustered, we can see large variations in the present bias and risk preference parameters. To investigate determinants of these parameters, we combine data of home and livelihood damage caused by the earthquake and tsunami, which are supposed to be exogenously determined.

Table 6.2: Summary Statiistics w.o. Outliers

Variable	Obs	Mean	Std. Dev.	P5	P10	P25	P50	P75	P90	P95
presentbias	185	1.25	1.069	.572	.752	.927	1.055	1.218	1.854	1.854
discountfactor	185	1.006	.028	.988	.994	.997	1.001	1.005	1.017	1.078
curvature	185	.785	.51	.018	.213	.731	.908	.935	.958	.966

In Iwanuma city, local government conducted metrical surveys and issued formal certificates for housing damage, with which households could obtain government compensation. During our experiments and in the main survey conducted in November 2013, we asked the participants about the level of housing damage. A cross tabulation of these damage levels is shown in Table 6.3 where ”today” refers to the data obtained in our experiments and ”half a year ago” refers to the data obtained from the main survey in November 2013. The different levels of damage are: totally collapsed or zenkai (5); almost collapsed or daikibohankai (4); half collapsed or hankai (3); minor damage or ichibu sonkai (2); or no damage (1). As shown in Table 6.4, we also collected data on subjective assessments of livelihood changes before and after the earthquake and tsunami, ranging from worsened (4); somewhat worsened (3); almost the same (2); and relatively improved (1).

Table 6.3: Today by half a year ago

	half_a_year_ago					
today	1	2	3	4	5	Total
1	19	0	0	0	0	19
2	2	13	2	0	0	17
3	0	3	17	1	0	21
4	1	0	3	50	25	79
5	0	0	0	7	41	48
Total	22	16	22	58	66	184

Source: Data in Iwanuma Experiment

Table 6.4: The Economic Condition

Item	Number	Per cent
1	3	2
2	113	62
3	48	26
4	18	10
Total	182	100

Source: Data in Iwanuma Experiment

To examine the impact of disasters, we re-estimate the CTB model allowing a heterogenous risk aversion parameter, α; time discounting parameter, δ; and present bias parameter, β, depending on the house damage level and livelihood change status. The results are presented in Table 6.5, where the subscript indicates the level of damage or change. Columns (1) and (2) allows heterogenous parameters based on house damage captured during the experiments and the main survey, respectively. Column (3) shows the results with heterogenous livelihood change impacts on the preference parameters. As we can see, the disaster affected the present bias parameter negatively. The disaster damage seems to make individuals slightly more present-biased, although, strictly speaking, the change caused by the disaster damage is not necessarily statistically significant.

Table 6.5: CTB results of Each Individual Group

	(1) *today*	(2) *half_a_year_ago*	(3) *economic_condition*
β_1	1.040***	1.039***	1.077***
	(0.0397)	(0.0299)	(0.0465)
β_2	1.018***	1.011***	1.039***
	(0.0252)	(0.0333)	(0.0212)
β_3	1.033***	0.993***	0.976***
	(0.0645)	(0.0452)	(0.0335)
β_4	0.960***	1.002***	0.898***
	(0.0539)	(0.0842)	(0.0811)
β_5	0.948***	0.955***	
	(0.0675)	(0.0549)	
δ_1	1.001***	1.000***	1.011***
	(0.00124)	(0.000886)	(0.00294)
δ_2	1.001***	1.001***	1.001***
	(0.000852)	(0.00122)	(0.000809)
δ_3	1.003***	1.004***	1.002***
	(0.00198)	(0.00167)	(0.00104)
δ_4	1.002***	1.003***	1.000***
	(0.00242)	(0.00188)	(0.00173)
δ_5	1.001***	1.000***	
	(0.00165)	(0.00153)	
α_1	0.888***	0.899***	0.820***
	(0.0140)	(0.0102)	(0.0439)
α_2	0.900***	0.890***	0.893***
	(0.00900)	(0.0125)	(0.00807)
α_3	0.878***	0.895***	0.909***
	(0.0223)	(0.0163)	(0.00950)
α_4	0.886***	0.845***	0.893***
	(0.0222)	(0.0291)	(0.0189)
α_5	0.914***	0.920***	
	(0.0111)	(0.00986)	
$\beta_1 = \cdots = \beta_5$	0.642	0.467	
$\beta_1 = \cdots = \beta_4$			0.101
$\delta_1 = \cdots = \delta_5$	0.818	0.314	
$\delta_1 = \cdots = \delta_4$			0.0075
$\alpha_1 = \cdots = \alpha_5$	0.467	0.078	
$\alpha_1 = \cdots = \alpha_4$			0.1870
N	4402	4450	4330

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2. Dictator Game Results

In addition to the CTB experiments, we conducted a dictator came experiment to elicit altruism. In the dictator game, the sender, called the "dictator," is provided with JPY 5,000 in 1,000 yen notes as the initial endowment that he/she can either keep or allocate to the receiver. Hence, the dictator must decide the transfer amount to his receiver from the possible transfer amounts of 0; 1,000; 2,000; 3,000; 4,000; or 5,000 yen. Since there is no self-interested reason for the sender to transfer money, the sender's zero transfers satisfy the Nash equilibrium. Hence, the actual positive amount of transfer is interpreted as the level of altruism (Camerer and Fehr, 2004; Levitt and List, 2009). We also adopt strategy methods, asking all participants as a sender the amounts they would send to each of three potential partners. Three partners are: a randomly selected person in the same residential area, a randomly selected victim of the Great East Japan Earthquake of March 2011, and a randomly selected person from Japan. Table 6.6 presents summary statistics of the amounts sent in the dictator games. We can see a substantial premium on altruism toward victims of the disaster in and outside Iwanuma city.

Table 6.6: Summary Statistics

Variable	Mean	Std. Dev.	N
donation_japan	1811.828	1244.26	186
donation_Iwanuma	2548.913	1120.011	184
donation_Earthquake	2792.35	1084.631	183

To investigate how the partner affects the subjects' responses and how damage suffered changes their responses, we postulate the following regression equation:

$$Donation_{ij} = \beta_0 + \beta_1 Partner_{ij} + \beta_2 Damage_i + \beta_3 Partner_{ij} \times Damage_i + \beta_4 X_i + \epsilon_{ij} \quad (5)$$

where $Donation_{ij}$ is the amount the subject *i* gives to partner *j* in the dictator game, $Partner_{ij}$ is a dummy variable which indicates who is the partner, $Damage_i$ is a dummy variable which indicates whether the subject is affected by the disaster, X_{ij} is a control variable and ϵ_{ij} is an error term. We capture the damage by house damage described above.

Results without and with preference parameters are shown in Tables 6.7 and 6.8, respectively. While the amounts sent to victims of the Great East Japan Earthquake are larger than those sent to an anonymous person in Japan. The damage level, however, does not generate a clear pattern in terms of the sending amount. In Table 6.8, present bias parameter and time discount factor are both negatively related to the amount of donation, implying that seemingly altruistic behaviours might be based on myopia.

Table 6.7: The Relationship between the Amount of Donation and Earthquakes

	(1) donation	(2) donation	(3) donation
$today = 2$	-174.1		
	(568.2)		
$today = 3$	-443.0		
	(624.2)		
$today = 4$	-446.6		
	(532.8)		
$today = 5$	-451.8		
	(632.7)		
$Iwanuma$	428.6	400.0	1250.0*
	(514.3)	(370.4)	(568.1)
$Earthquake$	571.4	700.0^{+}	1750.0**
	(359.2)	(365.9)	(568.1)
$today = 2 \times Iwanuma$	-678.6		
	(538.9)		
$today = 2 \times Earthquake$	-571.4		
	(359.2)		
$today = 3 \times Iwanuma$	308.8		
	(620.6)		
$today = 3 \times Earthquake$	165.9		
	(497.8)		
$today = 4 \times Iwanuma$	285.7		
	(561.1)		
$today = 4 \times Earthquake$	722.9		
	(471.6)		
$today = 5 \times Iwanuma$	79.86		

	(563.9)		
$today = 5 \times Earthquake$	183.4		
	(470.0)		
$Date$	373.6	340.3	426.8
	(323.7)	(325.9)	(287.0)
$harf\_a\_year = 2$		166.0	
		(572.0)	
$harf\_a\_year = 3$		-375.2	
		(614.2)	
$harf\_a\_year = 4$		-131.5	
		(514.5)	
$harf\_a\_year = 5$		-65.71	
		(526.2)	
$harf\_a\_year = 2 \times Iwanuma$		-800.0^{+}	
		(436.2)	
$harf\_a\_year = 2 \times Earthquake$		-700.0^{+}	
		(365.9)	
$harf\_a\_year = 3 \times Iwanuma$		100.0	
		(494.7)	
$harf\_a\_year = 3 \times Earthquake$		-200.0	
		(491.3)	
$harf\_a\_year = 4 \times Iwanuma$		348.5	
		(472.2)	
$harf\_a\_year = 4 \times Earthquake$		875.8^{+}	
		(516.6)	
$harf\_a\_year = 5 \times Iwanuma$		155.2	
		(417.3)	

$harf\_a\_year = 5 \times Earthquake$		-65.19	
		(438.4)	
$condition = 2$			225.6
			(1116.6)
$condition = 3$			-214.6
			(1101.5)
$condition = 4$			-631.1
			(1261.8)
$condition = 2 \times Iwanuma$			-916.7
			(596.2)
$condition = 2 \times Earthquake$			-1000.0
			(622.8)
$condition = 3 \times Iwanuma$			-622.1
			(606.9)
$condition = 3 \times Earthquake$			-844.8
			(623.8)
$condition = 4 \times Iwanuma$			-1583.3*
			(635.0)
$condition = 4 \times Earthquake$			-1416.7*
			(635.0)
_cons	2018.9***	1761.8***	1679.9
	(516.4)	(471.8)	(1146.6)
N	185	185	185

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6.8: The Relationship between the amount of Donation and Deep Parameters

	(1) donation	(2) donation	(3) donation
presentbias	-157.8*	-160.7**	-120.1^{+}
	(62.77)	(59.87)	(62.47)
discountfactor	-14850.3***	-14942.1***	-13770.5***
	(2444.3)	(2349.4)	(3071.0)
curvature	-241.6	-136.2	-9.413
	(299.1)	(259.7)	(276.3)
$today = 2$	-93.16		
	(621.3)		
$today = 3$	-496.5		
	(671.4)		
$today = 4$	36.54		
	(592.0)		
$today = 5$	157.4		
	(636.8)		
$Iwanuma$	428.6	400.0	1250.0*
	(524.4)	(377.6)	(578.9)
$Earthquake$	571.4	700.0^{+}	1750.0**
	(366.2)	(373.0)	(578.9)
$today = 2 \times Iwanuma$	-678.6		
	(549.5)		
$today = 2 \times Earthquake$	-571.4		
	(366.2)		
$today = 3 \times Iwanuma$	321.4		
	(687.5)		
$today = 3 \times Earthquake$	178.6		

	(576.0)		
$today = 4 \times Iwanuma$	312.2		
	(574.9)		
$today = 4 \times Earthquake$	724.9		
	(484.3)		
$today = 5 \times Iwanuma$	56.50		
	(575.8)		
$today = 5 \times Earthquake$	172.2		
	(482.9)		
$Date$	723.9*	608.8*	547.3^{+}
	(301.9)	(299.9)	(293.1)
gender	157.1	181.5	208.8
	(298.7)	(272.1)	(312.8)
age	788.6	867.6^{+}	657.1
	(477.8)	(504.2)	(470.4)
age2	-5.694^{+}	-6.164^{+}	-4.710
	(3.113)	(3.289)	(3.074)
$half\_a\_year = 2$		444.2	
		(566.0)	
$half\_a\_year = 3$		-10.57	
		(557.1)	
$half\_a\_year = 4$		362.4	
		(574.6)	
$half\_a\_year = 5$		413.1	
		(516.4)	
$half\_a\_year = 2 \times Iwanuma$		-800.0^{+}	
		(444.8)	

$half\_a\_year = 2 \times Earthquake$	-700.0^{+}	
	(373.0)	
$half\_a\_year = 3 \times Iwanuma$	100.00	
	(504.4)	
$half\_a\_year = 3 \times Earthquake$	-200.0	
	(501.0)	
$half\_a\_year = 4 \times Iwanuma$	389.5	
	(491.8)	
$half\_a\_year = 5 \times Earthquake$	878.9	
	(542.3)	
$half\_a\_year = 5 \times Iwanuma$	142.4	
	(426.3)	
$half\_a\_year = 5 \times Earthquake$	-73.09	
	(448.1)	
$condition = 2$		-26.66
		(1183.7)
$condition = 3$		-153.9
		(1121.5)
$condition = 4$		-77.74
		(1262.4)
$condition = 2 \times Iwanuma$		-916.7
		(607.6)
$condition = 2 \times Earthquake$		-1000.0
		(634.6)
$condition = 3 \times Iwanuma$		-601.6
		(622.2)
$condition = 3 \times Earthquake$		-837.8
		(640.2)

$condition = 4 \times Iwanuma$			-1583.3*
			(647.1)
$condition = 4 \times Earthquake$			-1416.7*
			(647.1)
_cons	-10242.1	-13711.3	-7092.7
	(18481.4)	(19337.2)	(18753.9)
N	182	182	182

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.3. Behaviours

Existing studies in behavioural economics attribute undesirable behaviours such as obesity, over-eating, debt overhang, gambling, smoking, drinking, and other procrastination behaviours to naive hyperbolic discounting (Banerjee and Mullainathan, 2010). In our data, we can verify whether and how individual preferences are related to real-world decisions and other subjective responses. The estimation results are shown in Table 6.9, 6.10, and 6.11, and suggest an insignificant relationship between the present bias parameter and behaviours. The only exception is the level of residential- area specific general trust captured by the General Social Survey (GSS) type subjective assessment (column [P30 1] in Table 6.9). The coefficient is marginally significant. The qualitative result indicates that present bias coincides with a high level of trust between people in the same community, suggesting that present bias is closely related to bonding social capital within each community. Yet, it is not necessarily clear whether this observed relationship is driven by naive or sophisticated hyperbolic discounting.

Table 6.9: The Relationship between Questions and Deep Parameters (Orders Probit)

	(1) P30 1)	(2) P30 2)	(3) P30 3)	(4) P31 1)	(5) P31 2)	(6) P31 3)	(7) P32 1)
main							
presentbias	0.0897	-0.0567	0.0319	-0.102	-0.0160	-0.0509	-0.0244
	(0.0562)	(0.0635)	(0.0595)	(0.0828)	(0.0427)	(0.0467)	(0.0433)
discountfactor	1.199	1.620	-4.211^{+}	2.347	0.703	3.486	1.718
	(2.447)	(2.959)	(2.303)	(3.152)	(2.351)	(2.630)	(2.558)
curvature	0.0645	0.386	0.185	-0.117	-0.219	0.00244	-0.0704
	(0.280)	(0.266)	(0.263)	(0.222)	(0.180)	(0.238)	(0.198)
gender	0.390*	-0.200	-0.0255	-0.0395	-0.483**	-0.272^{+}	-0.821***
	(0.184)	(0.173)	(0.173)	(0.164)	(0.164)	(0.165)	(0.169)
age	-0.0203	-0.0620	-0.139	-0.117	-0.696*	-0.244	0.0149
	(0.350)	(0.359)	(0.316)	(0.286)	(0.304)	(0.260)	(0.216)
age2	-0.0000078	0.00022	0.00073	0.00071	0.0046*	0.0016	-0.00015
	(0.0023)	(0.0024)	(0.0021)	(0.0019)	(0.0020)	(0.0017)	(0.0014)
cut1							
_cons	-1.203	-2.838	-10.89	-4.552	-27.65*	-7.639	0.611
	(13.66)	(13.95)	(12.28)	(11.49)	(11.58)	(10.18)	(8.816)
cut2							
_cons	0.956	-1.128	-9.388	-4.002	-26.68*	-6.768	1.435
	(13.65)	(13.95)	(12.28)	(11.49)	(11.57)	(10.16)	(8.810)
cut3							
_cons	2.012	-0.261	-8.704	-3.565	-26.26*	-6.482	1.912
	(13.67)	(13.95)	(12.25)	(11.50)	(11.57)	(10.16)	(8.811)
cut4							
_cons	2.380	1.061	-7.687	-3.055	-25.85*	-5.614	2.733
	(13.71)	(14.11)	(12.25)	(11.50)	(11.57)	(10.15)	(8.808)
cut5							
_cons				-2.259	-25.58*	-5.221	3.443
				(11.50)	(11.57)	(10.14)	(8.807)
N	178	178	178	170	174	174	177

Standard errors in parentheses

Standard errors in parentheses : $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6.10: The Relationship between Questions and Deep Parameters (continued)(Orders Probit)

	(1) P32 2)	(2) P34 1)	(3) P34 2)	(4) P34 3)	(5) P35 1)	(6) P36 2)
main						
presentbias	0.0972	-0.0141	0.0870	0.106	0.0747	0.0152
	(0.0844)	(0.0802)	(0.0965)	(0.0791)	(0.0919)	(0.0592)
discountfactor	2.090	3.296	-3.541	-3.987	-1.340	-3.597
	(3.182)	(3.601)	(2.853)	(3.645)	(2.585)	(2.457)
curvature	0.128	-0.100	-0.407	-0.147	-0.109	0.0485
	(0.225)	(0.318)	(0.316)	(0.300)	(0.257)	(0.357)
gender	0.648^{***}	0.202	0.363^{+}	0.0572	-0.323^{+}	0.230
	(0.184)	(0.194)	(0.201)	(0.200)	(0.186)	(0.183)
age	0.592^{+}	-0.373	0.0649	-0.0771	0.00275	0.759^{*}
	(0.319)	(0.360)	(0.350)	(0.360)	(0.366)	(0.351)
age2	-0.00390^{+}	0.00259	-0.0000103	0.000427	-0.0000460	-0.00523^{*}
	(0.00212)	(0.00240)	(0.00235)	(0.00239)	(0.00243)	(0.00233)
_cons				7.776		
				(14.04)		
cut1						
_cons	23.09	-11.28	-1.021		-3.171	21.95
	(12.36)	(13.92)	(12.78)		(13.92)	(13.40)
cut2						
_cons	23.55	-10.49	0.631		-1.117	22.90
	(12.37)	(13.93)	(12.83)		(13.92)	(13.36)
cut3						
_cons	24.55^{*}					25.13
	(12.40)					(13.37)
cut4						
_cons	25.04^{*}					26.16
	(12.41)					(13.38)
N	179	175	177	175	176	179

Standard errors in parentheses

Standard errors in parentheses : $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6. Concluding Remarks

Several important findings emerge from our study. First, we found that we cannot reject the null hypothesis in which the estimated present bias parameter equals one, indicating the absence of quasi-hyperbolic discounting in the whole sample. The estimated time discount rate is close to zero and the estimated risk aversion parameter is within a reasonable range. Overall, we can safely say that the subjects drawn from Iwanuma city are forward-looking and patient and without tendencies of quasi-hyperbolic discounting. Yet, the estimated individual-level preference parameters show that, while discount factor and risk parameters are clustered, there are large variations in the present bias and risk preference parameters. Secondly, we found that the disaster affected the present bias parameter negatively. The disaster damage seems to have made individuals more present-biased. Third, in dictator games, the amounts sent to victims of the Great East Japan Earthquake are larger than those sent to arbitrary persons in Japan. The damage level, however, does not generate a clear pattern in terms of the sending amount. Also, we found that present bias parameter and time discount factor are both negatively related to the amount of donation, implying that seemingly altruistic behaviours might be driven by myopic preference.

Since existing studies attribute undesirable behaviours such as obesity, over-eating, debt overhang, gambling, smoking, drinking, and other procrastination behaviours to naive hyperbolic discounting (Banerjee and Mullainathan, 2010), in our data, we investigate whether and how individual preferences are related to real-world decisions and other subjective responses. According to our estimation results, relationships between the present bias parameter and behaviours are largely insignificant statistically. The only exception is the level of residential area-specific general trust captured by the General Social Survey (GSS) type subjective assessment questions. This result implies that present bias coincides with a high level of trusting people within the same community, suggesting that present bias is closely related to bonding social capital within each community. However, it is not necessarily clear that this revealed relationship is driven by naive or sophisticated hyperbolic discounting. To verify the internal and external validity of the findings presented in this paper, future studies to examine the impact of disasters on individual and social preferences will be needed.

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Appendix

Figure 6.A.1: The Histogram of the Damage

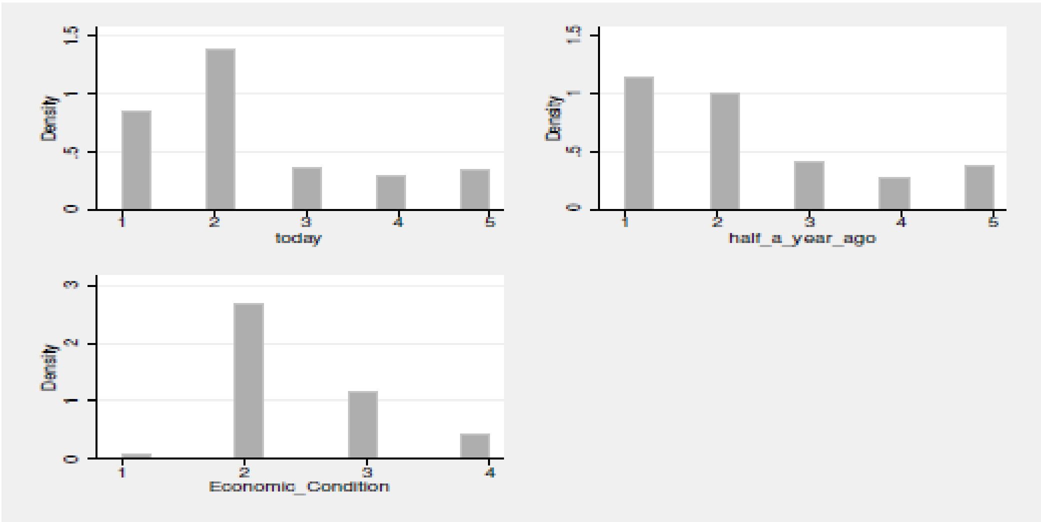

Figure 6.A.2: The Histogram of the Amount of Donation

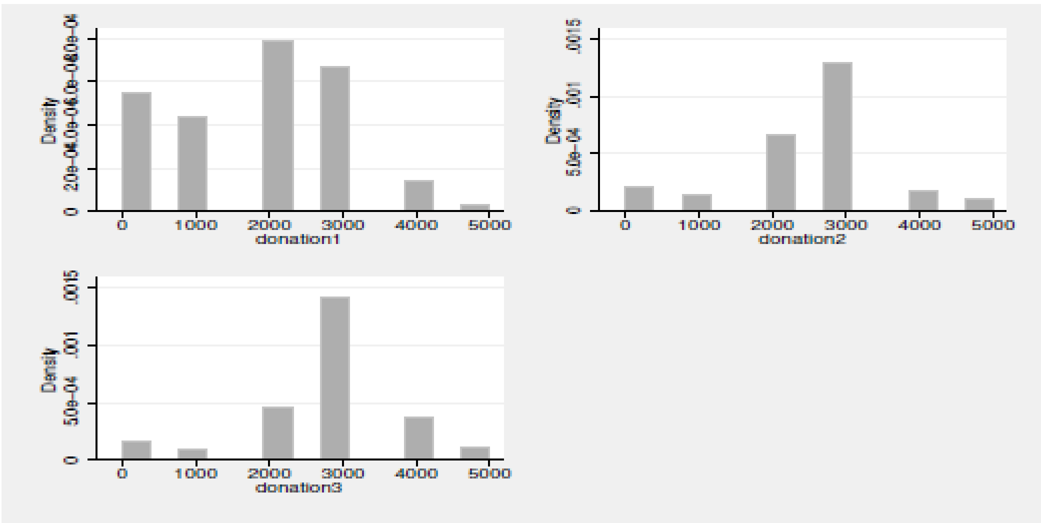

Figure 6.A.3: The Cumulative Distribution Function (CDF) of Present-bias with Respect to Today's Damage

cum1 ··· no change, cum2 ··· minor damage, cum3 ··· partial damage, cum4 ··· partial damage in a large scale, cum5 ··· complete damage

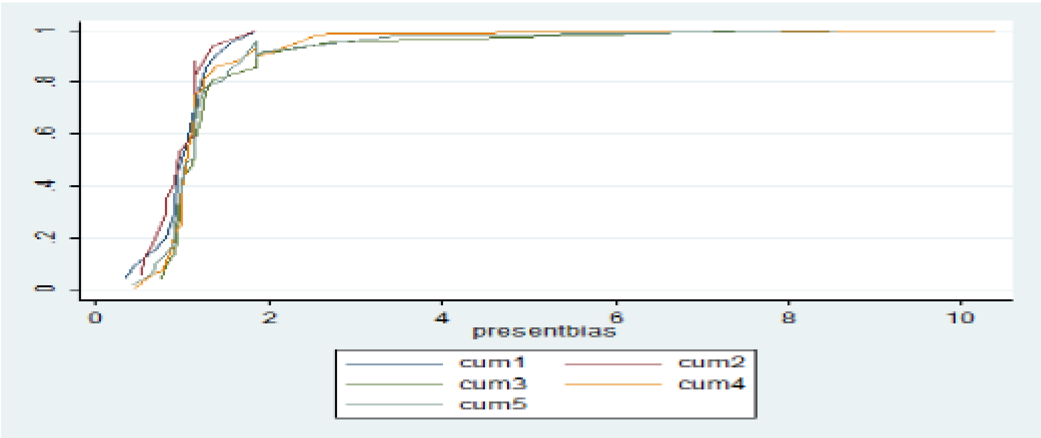

Figure 6.A.4: The CDF of Discount Factor with Respect to Today's Damage

cum1 ··· no change, cum2 ··· minor damage, cum3 ··· partial damage, cum4 ··· partial damage in a large scale, cum5 ··· complete damage

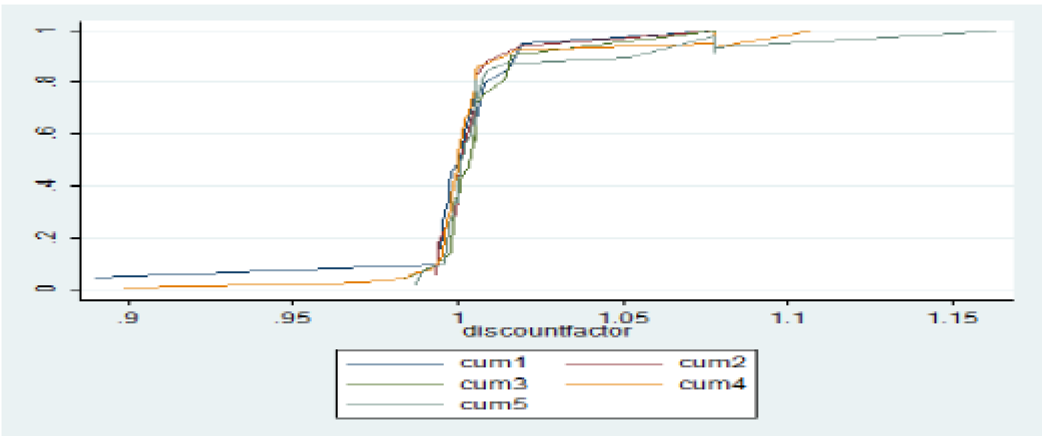

Figure 6.A.5: The CDF of Curvature with Respect to Today's Damage

cum1 ··· no change, cum2 ··· minor damage, cum3 ··· partial damage, cum4 ··· partial damage in a large scale, cum5 ··· complete damage

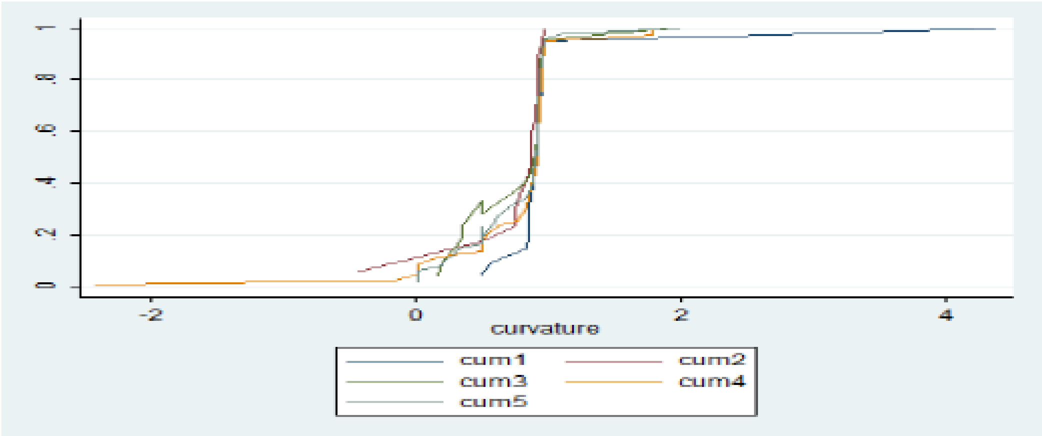

Figure 6.A.6: The CDF of Present-bias with Respect to half a year ago's Damage

cum1 ··· no change, cum2 ··· minor damage, cum3 ··· partial damage, cum4 ··· partial damage in a large scale, cum5 ··· complete damage

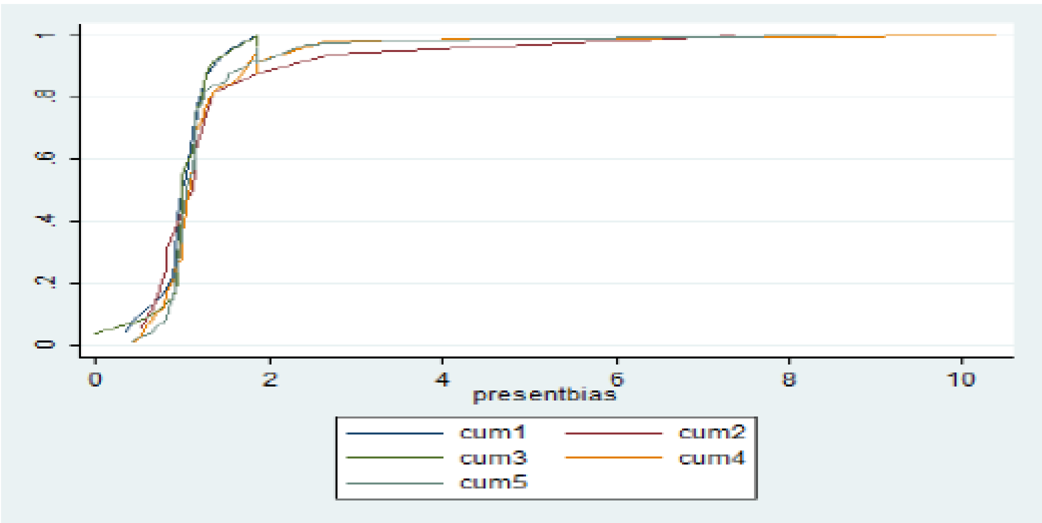

Figure 6.A.7: The CDF of Discount Factor with Respect to half a year ago's Damage

cum1 ⋯ no change, cum2 ⋯ minor damage, cum3 ⋯ partial damage, cum4 ⋯ partial damage in a large scale, cum5 ⋯ complete damage

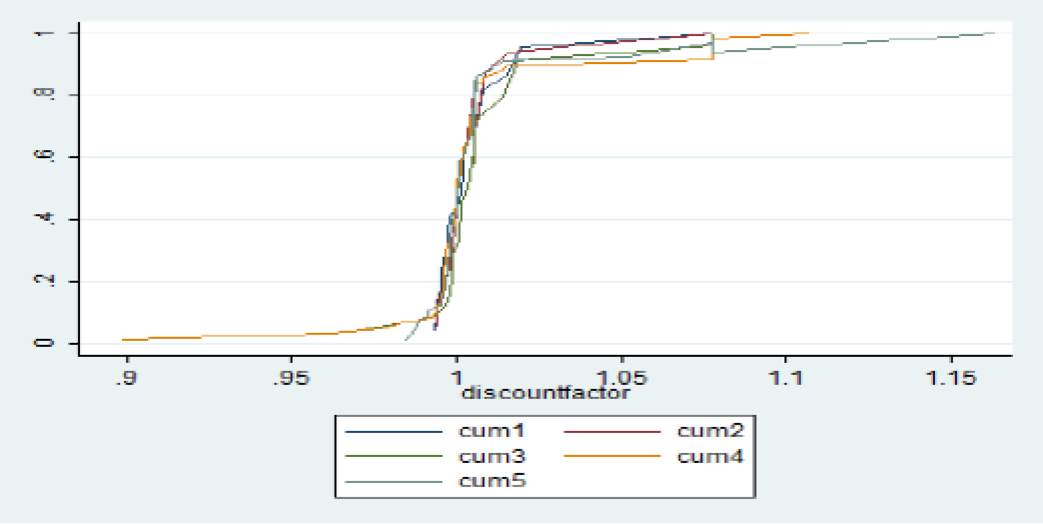

Figure 6.A.8: The CDF of Culvature with Respect to half a year ago's Damage

cum1 ⋯ no change, cum2 ⋯ minor damage, cum3 ⋯ partial damage, cum4 ⋯ partial damage in a large scale, cum5 ⋯ complete damage

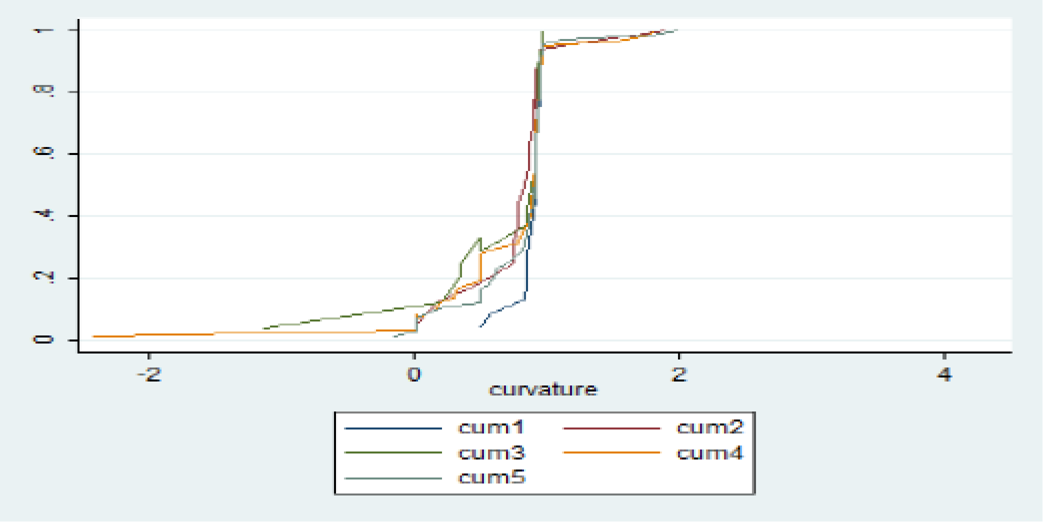

Figure 6.A.9: The CDF of Present-bias with Respect to Today's Economic Condition

cum1 ··· a little well, cum2 ··· no change, cum3 ··· a little bad, cum4 ··· bad

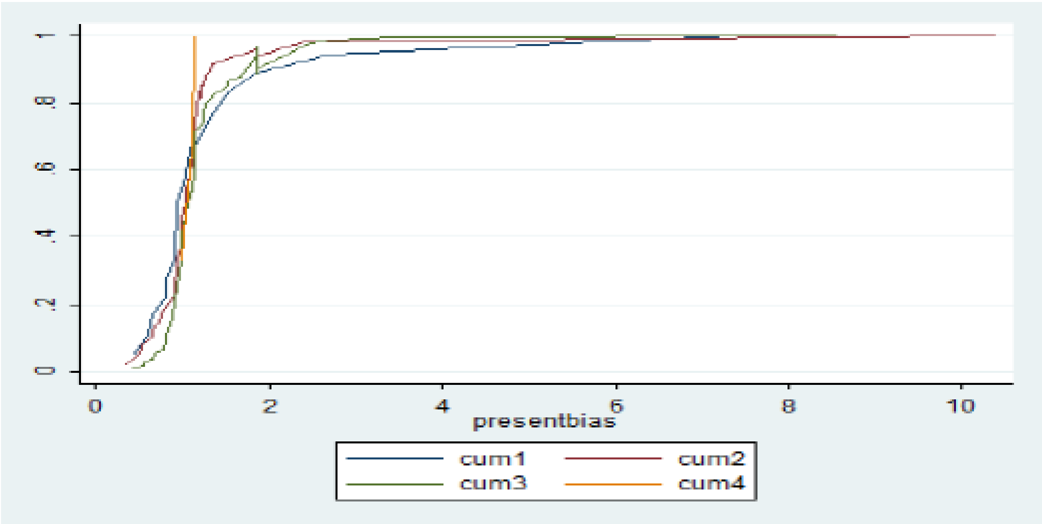

Figure 6.A.10: The CDF of Discount Factor with Respect to Today's Economic Condition

cum1 ··· a little well, cum2 ··· no change, cum3 ··· a little bad, cum4 ··· bad

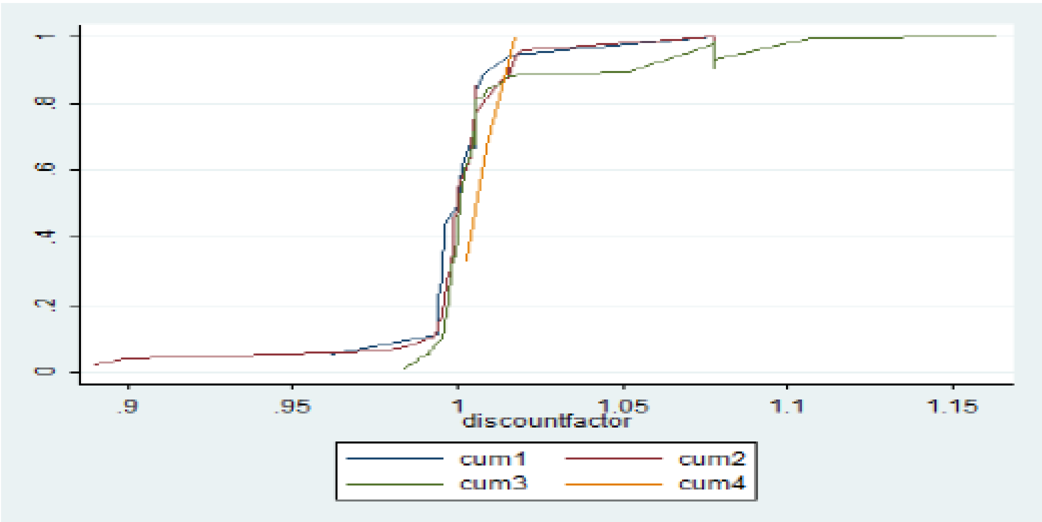

Figure 6.A.11: The CDF of Culvature with Respect to Today's Economic Condition

cum1 ⋯ a little well, cum2 ⋯ no change, cum3 ⋯ a little bad, cum4 ⋯ bad

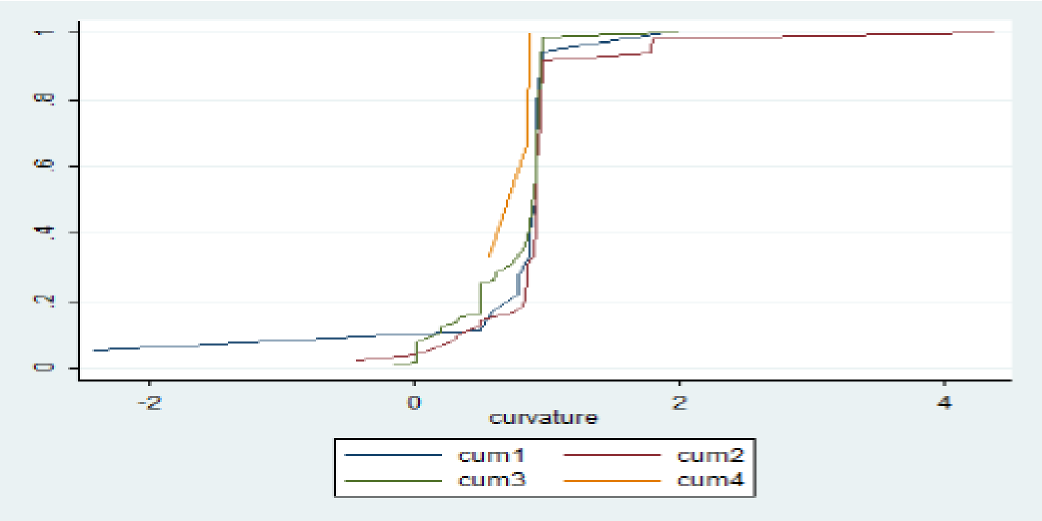

Table 6.A.1: The Relationship between Question and Deep Parameters (Linear Regression)

	(1) P30 1)	(2) P30 2)	(3) P30 3)	(4) P31 1)	(5) P31 2)	(6) P31 3)	(7) P32 1)
presentbias	0.0334	-0.0424	0.0120	-0.168	-0.0213	-0.0811	-0.0378
	(0.0296)	(0.0431)	(0.0470)	(0.133)	(0.0726)	(0.0741)	(0.0569)
discountfactor	0.233	1.340	-3.258*	2.971	2.255	5.060	3.080
	(1.307)	(2.318)	(1.499)	(3.900)	(3.672)	(3.745)	(3.322)
curvature	0.0413	0.307+	0.131	-0.0793	-0.418	-0.00609	-0.116
	(0.138)	(0.180)	(0.181)	(0.272)	(0.281)	(0.342)	(0.255)
gender	0.188+	-0.155	-0.0628	-0.193	-0.784**	-0.430+	-1.036***
	(0.0977)	(0.128)	(0.132)	(0.206)	(0.251)	(0.230)	(0.207)
age	-0.0827	-0.0597	-0.128	-0.102	-1.091*	-0.434	0.0865
	(0.224)	(0.267)	(0.234)	(0.369)	(0.431)	(0.394)	(0.289)
age2	0.000470	0.000264	0.000714	0.000592	0.00719*	0.00286	-0.000651
	(0.00146)	(0.00176)	(0.00154)	(0.00243)	(0.00283)	(0.00260)	(0.00188)
_cons	5.234	3.832	10.74	6.385	43.80**	15.71	-2.424
	(8.804)	(10.49)	(9.033)	(14.39)	(16.51)	(15.12)	(11.84)
N	178	178	178	170	174	174	177

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6.A.2: The Relationship between Question and Deep Parameters (continued) (Linear Regression)

	(1)	(2)	(3)	(4)	(5)	(6)
	P32 2)	P34 1)	P34 2)	P34 3)	P35 1)	P36 2)
presentbias	0.0850	-0.00958	0.0258	0.0264	0.0325	-0.000539
	(0.0632)	(0.0506)	(0.0235)	(0.0184)	(0.0399)	(0.0343)
discountfactor	1.961	1.699	-1.282	-1.320	-0.636	-1.542
	(2.500)	(1.835)	(1.201)	(1.307)	(1.195)	(1.330)
curvature	0.118	-0.0210	-0.151	-0.0517	-0.0472	0.0598
	(0.225)	(0.183)	(0.114)	(0.105)	(0.124)	(0.221)
gender	0.614^{***}	0.104	0.141^{+}	0.0214	-0.156^{+}	0.102
	(0.170)	(0.106)	(0.0790)	(0.0734)	(0.0869)	(0.0989)
age	0.566^{+}	-0.159	0.0992	-0.0289	0.000888	0.446^{*}
	(0.308)	(0.161)	(0.120)	(0.127)	(0.176)	(0.215)
age2	-0.00371^{+}	0.00111	-0.000509	0.000161	-0.0000176	-0.00306^{*}
	(0.00205)	(0.00105)	(0.000786)	(0.000848)	(0.00117)	(0.00143)
_cons	-19.89^{+}	6.496	-0.565	3.243	2.024	-11.73
	(11.81)	(6.566)	(4.670)	(5.040)	(6.694)	(8.123)
N	179	175	177	175	176	179

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6.A.3: The Relationship between the Amount of Public Money and the Number of Neighborhood

	(1) publicmoney	(2) publicmoney
group = 1	206.4**	209.7**
	(77.83)	(78.10)
neighbourhood = 1	-220.4	-205.9
	(207.3)	(205.2)
neighbourhood = 2	518.3	576.3
	(483.3)	(486.7)
neighbourhood = 3	139.4	97.87
	(146.9)	(170.4)
neighbourhood = 4	-1762.7***	-1675.2***
	(304.4)	(322.1)
age	-608.9+	-541.2
	(340.4)	(338.5)
age2	3.891+	3.446
	(2.258)	(2.247)
gender	-289.5	-296.0
	(181.2)	(183.8)
presentbias		105.9*
		(46.27)
discountfactor		5293.1
		(3464.9)
curvature		-19.74
		(228.7)
_cons	26587.8*	18590.1
	(12782.2)	(13446.8)
N	355	351

Standard errors in parentheses : $^{+}$ p < 0.10, * p <0.05, ** p<0.01, *** p< 0.001

Table 6.A.4: The Relationship between the Amount of Public Money, the Number of Neighborhood and the Amount of Donation

	(1) publicmoney	(2) publicmoney
$group = 1$	196.8*	197.4*
	(78.52)	(78.77)
$neighbourhood = 1$	-229.1	-217.8
	(198.9)	(193.9)
$neighbourhood = 2$	745.2	838.3+
	(465.9)	(484.8)
$neighbourhood = 3$	35.18	36.54
	(196.1)	(220.8)
$neighbourhood = 4$	-952.5*	-851.9+
	(474.4)	(475.4)
$dictator = 1000$	-612.3	-727.7+
	(429.9)	(422.1)
$dictator = 2000$	-448.1	-481.3
	(386.4)	(385.0)
$dictator = 3000$	-682.8+	-648.2+
	(360.2)	(357.3)
$dictator = 4000$	-1392.6**	-1370.2**
	(522.4)	(518.9)
$dictator = 5000$	-1050.3	-827.1
	(1022.4)	(1307.1)
age	-536.0	-456.1
	(336.3)	(320.9)
age2	3.352	2.813
	(2.233)	(2.130)
gender	-206.7	-197.2
	(184.5)	(192.2)
presentbias		117.6*
		(54.23)
discountfactor		4336.1
		(3190.9)
curvature		34.38
		(205.5)
_cons	24723.9*	17221.9
	(12522.8)	(12290.9)
N	353	349

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6.A.5: Tabulations of Responses to Hypothetical Time Preference Questions

	Indifferent between 20000 yen in 6 months and X in 7 months			
Indifferent between 20000 yen now and X in one months	Patient $X < 25000$	Somewhat Patient $25000 < X < 30000$	Most impatient $30000 < X$	Total
Patient	125	11	1	137
$X < 25000$	69.44 %	6.11 %	0.56 %	76.11 %
Somewhat Patient	9	12	5	26
$25000 < X < 30000$	5.00 %	6.67 %	2.78 %	14.44 %
Most impatient	2	5	10	17
$30000 < X$	1.11 %	2.78 %	5.56 %	9.44 %
Total	136	28	16	180
	75.56 %	15.56 %	8.89 %	100 %

Source: data1521.dta

Table 6.A.6: The Relationship between Subjective Hyperbolic Discounting and the Severity of the Damage

	(1) hyperbolic	(2) hyperbolic	(3) hyperbolic
today = 2	0.00619		0.0120
	(0.0524)		(0.0560)
today = 3	-0.0906*		-0.0822^{+}
	(0.0439)		(0.0496)
today = 4	0.0856		0.112
	(0.104)		(0.113)
today = 5	-0.0333		0.00771
	(0.0710)		(0.0897)
age	-0.0336	-0.0263	-0.0444
	(0.0677)	(0.0620)	(0.0669)
age2	0.000219	0.000175	0.000301
	(0.000439)	(0.000400)	(0.000434)
gender	0.00747	0.0256	0.0148
	(0.0478)	(0.0425)	(0.0470)
condition = 2		0.124*	0.173*
		(0.0545)	(0.0735)
condition = 3		0.0999	0.143^{+}
		(0.0616)	(0.0762)
condition = 4		0.0217	0.0639
		(0.0388)	(0.0644)
_cons	1.362	0.942	1.547
	(2.617)	(2.416)	(2.585)
N	180	178	178

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6.A.7: The Relationship between Subjective Hyperbolic Discounting and Temporary Residence

	(1) hyperbolic
temporary	0.0876
	(0.0926)
$today = 2$	0.00977
	(0.0561)
$today = 3$	-0.0930^{+}
	(0.0511)
$today = 4$	0.0969
	(0.109)
$today = 5$	-0.0638
	(0.105)
$condition = 2$	0.171*
	(0.0726)
$condition = 3$	0.144^{+}
	(0.0755)
$condition = 4$	0.0747
	(0.0629)
age	-0.0464
	(0.0671)
age2	0.000314
	(0.000436)
gender	0.0220
	(0.0457)
_cons	1.615
	(2.593)
N	178

Standard errors in parentheses : $^{+}$ p < 0.10, * p <0.05, ** p<0.01, *** p< 0.001

Table 6.A.8: The Relationship between Present-bias and Temporary Residence

	(1) presentbias	(2) presentbias
temporary	-0.242*	-0.225
	(0.112)	(0.140)
age	-0.538	-0.511
	(0.606)	(0.559)
age2	0.00370	0.00355
	(0.00413)	(0.00383)
gender	-0.205	-0.175
	(0.163)	(0.204)
$today = 2$		-0.160
		(0.210)
$today = 3$		0.0908
		(0.258)
$today = 4$		-0.288
		(0.196)
$today = 5$		-0.193
		(0.229)
$condition = 2$		0.369
		(0.476)
$condition = 3$		0.494
		(0.586)
$condition = 4$		0.595
		(0.716)
_cons	20.80	19.36
	(22.09)	(19.97)
N	180	176

Standard errors in parentheses

Standard errors in parentheses : $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$