European Economic Review 161 (2024) 104632

Contents lists available at ScienceDirect

European Economic Review

journal homepage: www.elsevier.com/locate/eer

On the stability of preferences: Experimental evidence from two disasters☆

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ARTICLE INFO

JEL classification:
C93
D81
O12

Keywords:
Convex time budget experiment
Multiple price list experiment
Disasters
Risk and time preference
Hyperbolic discounting

ABSTRACT

We investigate the impacts of two disasters in Japan and the Philippines on preferences using the convex time budget experiments and multiple price list experiments with monetary rewards. By exploiting natural experiments which are combined with lab-in-the-field experiments, we aim to investigate whether and how long preferences are affected by extreme events. We find evidence supporting preference instability caused by exposure to natural hazards: in both our study sites, disaster exposure seems to make individuals more present-biased even though they differ in socioeconomic conditions and disaster types. The estimated impacts are persistent over the short and long time intervals in both disaster-affected areas and are robust to the method of measuring preferences.

1. Introduction

The literature on the endogenous formation of individual preferences reveals that these preferences are not constant across time, and they change under some circumstances (Fehr and Hoff, 2011). Since natural hazards are traumatic events, exposure to them are likely to affect an individual's preference and behavior. However, the empirical findings are mixed and inconclusive (Chuang and Schechter, 2015; Schildberg-Hörisch, 2018). For example, Bchir et al. (2013), Bourdeau-Brien and Kryzanowski (2020), Cameron and Shah (2015) and Cassar et al. (2017) consider the cases of Peru, the U.S., Indonesia and Thailand, respectively, finding that exposure to natural hazards make people more risk averse. In contrast, results of Eckel et al. (2009) on a hurricane in the U.S., Hanaoka et al. (2018) on an earthquake in Japan, and Page et al. (2014) on floods in Australia show that victims become less risk averse systematically. Moreover, Becchetti et al. (2017) finds no change in risk aversion in those exposed to a tsunami in Sri

☆ We would like to thank our project members from the Philippines, Nobu Fuwa, Kei Kajisa, Takahiro Sato, Fe Gascon, and Ed Lucio. We are also grateful to the Iwanuma project members, Toyo Ashida, Hikichi Hiroyuki, Ichiro Kawachi, Katsunori Kondo, and Ken Osaka for their cooperation in the surveys and experiments. We would also like to thank the editor, associate editor, and two anonymous referees of this journal for very constructive comments which strengthened our paper substantially. We appreciate useful comments on the earlier versions of our paper at various seminars, workshops and conferences from Jim Andreoni, Nick Bloom, Jiahua Che, Syngjoo Choi, Federico Echenique, Lorenz Goette, Chie Hanaoka, Keigo Inukai, Hidehiko Ichimura, Taisuke Imai, Gaurav Khanna, Dean Karlan, Bryant Kim, Fukunari Kimura, Michael Kuhn, Jumgmin Lee, Jaimie Lien, Mushfiq Mobarak, Takeshi Murooka, Ilan Noy, Masao Ogaki, Fumio Ohtake, Kota Saito, Hitoshi Shigeoka, Yoshito Takasaki, Alessandra Voena, Yasutora Watanabe, Leeat Yariv, Joanne Yoong, Jie Zheng, and participants of JAGES study meetings, FY2013–2014 ERIA project meetings, 2014 Hayami Conference, 2015 World Congress of Econometric Society in Montreal, Canada, 2019 Yale-Nankai International Conference on Development Economics and 2nd Asian Workshop on Econometrics and Health Economics. The funding for this research has been provided by the Economic Research Institute for ASEAN and East Asia (ERIA), Indonesia as well as JSPS KAKENHI Grants-in-Aid for Scientific Research, Japan (Numbers 26220502 & 22K21341). The survey and experimental procedures were approved by the human subjects committees of the University of Tokyo (No. 13-165 for the East Laguna Village in FY2013; and No. 14-26 for Iwanuma city in FY2014). The authors are responsible for any remaining errors.

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https://doi.org/10.1016/j.euroecorev.2023.104632
Received 11 February 2022; Received in revised form 30 October 2023; Accepted 3 November 2023
Available online 4 November 2023

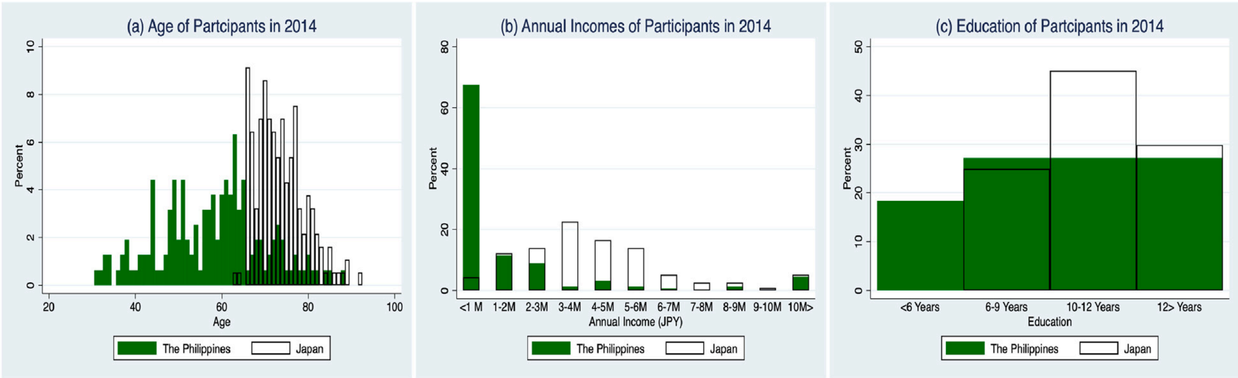

Fig. 1. Comparison of age, income and education levels.

Lanka. Concerning time discounting, although Callen (2015) finds that the Asian tsunami disaster in 2004 decreased impatience in Sri Lanka, it reinforced impatience in Thailand (Cassar et al., 2017) and present biasedness in the Philippines (Sawada and Kuroishi, 2015a) and Japan (Sawada and Kuroishi, 2015b; Akesaka, 2019).

The mixed empirical results have been attributed to the following three possible factors in the existing literature. First, subject's socioeconomic conditions, disaster types, and methods of eliciting preference parameters may generate seemingly inconclusive results (Schildberg-Hörisch, 2018). In other words, different disasters might have different effects on the preferences of people from different socioeconomic backgrounds. Hence, when studies on the spectrum of different disasters from diverse parts of the world show heterogeneous effects on the samples, it may be natural to observe differentiated effects.

Second, specification errors may exist in estimation (Vieider, 2018). While the underlying economic model requires the simultaneous incorporation of risk and time preferences (Andreoni and Sprenger, 2012; Andersen et al., 2008; Cheung, 2016), to the best of our knowledge, studies on the nexus between disasters and preferences have not considered the joint inference of all the parameters that collectively guide an individual's choices.[1] Additionally, failure to consider possible market frictions, such as binding liquidity constraints, can bias the estimated parameters (Carvalho et al., 2016; Dean and Sautmann, 2021).

Third, inaccurate data on disaster exposure and experimental results can generate systematic biases in estimating the impact of disasters on preferences, making it difficult to precisely identify causal relationships (Vieider, 2018; Schildberg-Hörisch, 2018). For example, disaster exposures and damage can be captured imprecisely due to subjective reporting bias (Higuchi et al., 2019) or the unavailability of data on individual-level disaster exposure (Hanaoka et al., 2018). Additionally, noisy experimental results can distort the estimation results if data quality is systematically correlated with the literacy, education, and cognitive capacity of the subjects (Andersson et al., 2016; Chakraborty et al., 2017; Schildberg-Hörisch, 2018). In this respect, a carefully designed lab experiment by Imas (2016) shows that a discrepancy between realized and non-realized losses makes parameter estimation systematically biased if these two types of losses are not properly distinguished.

While these points have been studied in the literature, there is little consensus on whether disaster exposure affects preferences persistently in the short-run and long-run periods. Since the lag between disaster exposure and preference measurement varies substantially, different studies could possibly yield different estimates of the effect of a disaster on preferences if such an effect exists only temporarily or changes over time.

Focusing on this preference instability in the time domain, our study aims to rigorously examine the short-term and long-term impacts of disaster exposure on the present bias, exponential time discounting, and curvature parameters (i.e., the intertemporal elasticity of substitution and the degree of risk aversion) of a utility function. For this purpose, we conduct lab-in-the-field experiments in Japan's Iwanuma city, which was hit by a strong earthquake and tsunami in 2011, and in the East Laguna Village in the Philippines,[2] which was affected by serious floods triggered by the monsoon ("habagat" in 2012). Preferences are elicited in an integrated manner with joint determination by two incentivized experiments with monetary rewards: the convex time budget (CTB) experiments developed by Andreoni and Sprenger (2012), Andreoni et al. (2015) and the multiple price list (MPL) experiment developed by Andersen et al. (2008). These experiments were conducted twice in both areas, approximately 2-3 and 6 years after each disaster. Accurate information on the damage, collected from government metrical surveys in Iwanuma city and from satellite images in East Laguna Village, as well as our sui generis survey data sets, which cover different disaster events in distinct settings in terms of the age, income, and educational profiles of subjects (Fig. 1), allows us to investigate whether and how the effect of a disaster on preferences tends to be long-lasting.

We believe that eliciting preference measurements over the same short and long time intervals from two independent sites affected by separate natural disasters is unique. Combined with the consistent and rigorous simultaneous estimation method, our

[1] For example, it is well known that elicitation of the time-discounting parameter using only a discounting multiple price list will seriously bias the estimate (Andersen et al., 2008; Cheung, 2016).

[2] For anonymity, we refer to this village as the East Laguna Village throughout the paper.

study would make a significant contribution to the literature because the existing studies predominantly report the short-time or long-time effect depending on their research time horizons.[3]

Our analysis leads to the following four findings. First, the application of the two experimental methods to the two distinctive disasters suggests that disaster exposure commonly makes individuals more present-biased in the two locations, despite their very different socioeconomic characteristics. Second, we find evidence supporting that this impact persisted at least for six years in both countries. Third, our main results may not necessarily be driven by variations in the educational level of subjects or by potential market frictions in the form of binding liquidity constraints. Rather, our results seem consistent with the psychological frameworks emphasized by Callen et al. (2014), Callen (2015). Finally, our findings are robust to the method of measuring preferences.

The rest of this paper is organized in the following way. Section 2 briefly overviews two disasters in Japan and the Philippines. In Section 3, we explain the parameter estimation strategies used in this study. Sections 4 and 5 present our findings from Japan and the Philippines, respectively. Section 6 presents results related to potential selection bias. Section 7 discusses the implications of our findings which is followed by the concluding remarks in the final section.

2. Two disasters and experiments

Our data are collected from Iwanuma city in Japan, which was hit by a strong earthquake and tsunami in 2011, and from the East Laguna Village, which was affected seriously by strong floods in 2012. Socioeconomic characteristics of subjects from these two communities are distributed very differently in terms of age, income, and educational level (Fig. 1).

2.1. The great East Japan earthquake

Concerning the data from Japan,[4] we employ three waves of panel survey in 2010, 2013, and 2016 in Iwanuma city of Miyagi Prefecture collected as part of the Japan Gerontological Evaluation Study (JAGES),[5] together with additional data we gathered from two rounds of the lab-in-the-field experiment implemented in Iwanuma city in 2014 and 2017. This is part of large-scale JAGES surveys which were conducted with 169,215 community-dwelling individuals aged 65 years or above residing in 31 municipalities of 12 Japanese prefectures from July 2010 to January 2012. Of these individuals, we selected JAGES respondents living in one of the 31 municipalities, Iwanuma city, which suffered considerable damages caused by the Great East Japan Earthquake on March 11, 2011 and the subsequent tsunami. In the city, 180 lives were lost, and 2766 homes were either destroyed or seriously damaged by the disasters. The proportion of the area submerged by the tsunami wave was the largest in Iwanuma city, among all the areas affected by the earthquake and tsunami. Thus, we considered JAGES survey's respondents in Iwanuma city as the best candidates to investigate the impact of disasters on individual preferences.

Unlike typhoons, epidemics, and man-made disasters, tsunamis and floods present a clear "discontinuous" variation of local damages in a homogeneous area with an unknown disaster border before the event, providing random assignments of "treatment" and "control" groups of disaster damages. We exploit this natural experimental situation to identify causal impacts of disasters on individual preferences. Of all the 2013 JAGES census respondents in Iwanuma city, 1023 residents agreed to participate in the experiments. Out of these people, we sent invitations to 346 respondents who lived along the tsunami border areas, which were unknown beforehand but became clear afterward. Eventually, a total of 186 individuals participated in our laboratory experiments in 2014.[6] We asked participants of our 2014 experiments to join again in the experiments in 2017. We also sent additional invitations to those who lived in the tsunami affected areas but had not participated in our 2014 experiments. Out of the 225 invitees, a total of 179 individuals participated in our field experiments in 2017.[7,8]

[3] While Eckel et al. (2009) finds the diminishing effect of disaster exposure on risk preferences within one year, Hanaoka et al. (2018) demonstrates increased risk-taking even five years after the disaster.

[4] Japan is vulnerable to a variety of natural disasters, such as earthquakes, tsunamis generated by earthquakes, volcanic eruptions, typhoons, floods, landslides, and avalanches. Of these natural disasters, earthquakes are the most serious and frequently occurring disasters. The continuous seismic activity is attributed to the country's location on a subduction zone, where four of the more than ten tectonic plates covering the globe are crushed against each other.

[5] JAGES aims to empirically survey risk factors for and social determinants of health and frailty (i.e., need for long-term care) among elderly people. It focused on those who did not already have a physical or cognitive disability, defined by not receiving public long-term care insurance benefits, as its baseline survey sample.

[6] We conducted a series of experiments on the following dates in 2014: May 15 (38 participants), May 16 (47 participants), May 19 (29 participants), May 20 (47 participants), and May 21 (25 participants).

[7] Among 186 individuals in our first laboratory experiment, 117 individuals also participated in our second laboratory experiment.

[8] In 2017, we conducted experiments on the following dates: February 8 (26 participants), February 9 (11 participants), February 10 (21 participants), February 11 (16 participants), February 14 (15 participants), February 21 (26 participants), February 27 (29 participants), February 28 (24 participants), March 28 (6 participants), and March 29 (5 participants).

2.2. Habagat in the Philippines

We also study residents in the East Laguna village which is located in approximately 80 kilometers towards south of Metro Manila, facing the east coast of the lake Laguna de Bay. Its proximity to the International Rice Research Institute (IRRI) has enabled researchers to conduct long-term panel surveys since 1966.[9]

In August 2012, the village was unexpectedly hit by serious out-of-season floods due to the southwest monsoon winds called "Habagat" and the resulting overflow of lake water. The floods negatively impacted rice production because the timing of the floods was detrimental to the crop's growth.[10] In the village data sets covering the last five decades, there has been no record of other floods at this scale (Estudillo, 2013).

In the East Laguna village's study, we employ the same type of surveys and experiments as the ones adopted for Iwanuma city. The subjects comprised farmers in the East Laguna village and the two surrounding villages. In 2014, a total of 158 farmers participated in our field experiments.[11] In 2018, a total of 141 farmers participated in our field experiments.[12]

3. Parameter estimation strategies

We employed Andreoni et al. (2015)'s CTB experiment twice, both in Japan (2014 and 2017) and the Philippines (2014 and 2018), and Andersen et al. (2008)'s MPL experiment once in Japan (2017) and twice in the Philippines (2014 and 2018).

3.1. The Convex Time Budget (CTB) experiment

The CTB experiment of Andreoni et al. (2015) allows us to separately identify the three key parameters of the time-separable CRRA utility function with the β-δ discounting (Strotz, 1955; Phelps and Pollak, 1968; Laibson, 1997)—the inverse of intertemporal elasticity of substitution, α; the exponential time discounting factor, δ; and the quasi-hyperbolic discounting factor showing present bias, β. This function is expressed as $U(x_t, x_{t+k}) = u(x_t) + \beta\delta^k u(x_{t+k})$ if $t = 0$; and $U(x_t, x_{t+k}) = \beta u(x_t) + \beta\delta^k u(x_{t+k})$ if $t \neq 0$, where $u(x_t) = \frac{x_t^{1-\alpha}}{1-\alpha}$, and the values x_t and x_{t+k} denote experimental earnings. While present bias is associated with $\beta < 1$, $\beta = 1$ and $\beta > 1$ correspond to the cases of standard exponential discounting and future bias, respectively.

In our experiments, each subject faces 24 convex budget decisions involving combinations of starting times, t; delay lengths, k; and annual interest rates, P. We combine three early payments' date, $t = (0, 35, 63)$ days from the experiment date (i.e., $t = 0$) and two time intervals, $k = (35, 63)$ days from the early payments' date, t. Specifically, we construct four (t, k) cells—(t, k)=(0, 35), (0, 63), (35, 70), and (63, 126); each cell contains six CTB questions with different payoffs and interest rates P, generating 24 choices for each subject.

Delayed payments were scheduled to arrive on the specified day exactly by mail in Iwanuma and in person in East Laguna Village for which we provided signed payment certificates and detailed contact numbers of the principal investigator in the case of Iwanuma and the local head investigator in the case of East Laguna Village. In Iwanuma, the experiments were organized with full endorsement by its city government which was stated in the invitation letters. To secure confidence of the subjects further, meeting rooms in the local government office were used for our experiments. The later payments were placed in the sealed envelope with the address of a subject on the day of each experiment. In East Laguna Village, the experiment team members were recruited from a pool of IRRI retirees who used to work for the village studies in the last few decades. In the signed certificates of future payments, we included detailed contact information of the head enumerator who has been known very well among the villagers. Before we let subjects make decisions, we explained these procedures repeatedly. Hence, we believe that uncertainties associated with future repayments are unlikely to affect decisions.

In each CTB question, subjects are given the choices between two corner points—(X, 0) and (0, Y)—in which X denotes the earliest and smallest payment, and Y denotes the latest and largest payment. Other three interior choices are located along the intertemporal budget constraint connecting these points such that $Px_t + x_{t+k} = Y$, where $P = \frac{Y}{X}$ represents the gross interest

[9] The earliest documented survey of the village dates back to 1966, when a Japanese geographer, Hiromitsu Umehara, carried out a census survey of the village (Umehara, 1967). Since then, 18 rounds of household surveys were conducted from 1974 to 2007, in collaboration with IRRI (Estudillo et al., 2010). Surveys in the 1970s, 1980s, and 1990s were organized mainly by Yujiro Hayami and Masao Kikuchi (Hayami and Kikuchi, 1999). Surveys in the 2000s were organized by other researchers (Fuwa, 2011; Kajisa, 2007). The village has been repeatedly surveyed, which has led to the collection, compilation, and analyses of useful benchmark information.

[10] Over an eight-day period, from August 1 to August 8, 2012, torrential rains and thunderstorms hit the Philippines. The effects centered on Metro Manila, the surrounding provinces of the Calabarzon region (Quezon, Cavite, Laguna, and Rizal provinces), and the provinces of Region III (Bulacan, Pampanga, and Bataan provinces). While the storm cannot be categorized as a typhoon, it was a strong movement of the southwest monsoon wind "Habagat" caused by the pull of the Typhoon Saola (Gener) from August 1 to August 3, 2012, and strengthened by the Typhoon Haikui. It caused typhoon-like damage, such as river overflow and landslides, to the entire region. In the Laguna province, where the East Laguna village is located, "Habagat" spawned flooding that submerged low-lying villages in 19 towns and cities, including the village, destroying P410.3 million worth of agricultural products. Comprising rice and corn, the damaged crops were planted in about 11,000 hectares of inundated farmlands; additionally, "Habagat" affected some 6000 farmers in the whole area. More than a half of the village area was submerged in flooded water, destroying paddy seriously.

[11] We conducted a series of experiments on the following dates in 2014: March 20 (33 participants), March 21 (33 participants), March 22 (36 participants), March 23 (39 participants), and March 24 (17 participants).

[12] In 2018, we conducted several experiments on the following dates: March 3 (31 participants), March 4 (36 participants), March 5 (25 participants), March 6 (29 participants), and March 7 (20 participants).

rate.[13] Given the intertemporal budget constraint, each subject maximizes own utility function. As Andreoni et al. (2015) shows, the first-order necessary condition of this maximization problem is a standard consumption Euler equation, which is log-linear in the experimental variations of t, k, and P:

$$ln(\frac{x_t}{x_{t+k}}) = -\frac{ln(\beta)}{\alpha}\mathbb{1}[t=0] - \frac{ln(\delta)}{\alpha}k - \frac{1}{\alpha}ln(P), \quad (1)$$

where $\mathbb{1}[t=0]$ is an indicator function which takes 1 if the argument is true and 0 otherwise. Assuming a well-behaved additive error term, this equation can be estimated at a group level or an individual level by the ordinary least squares (OLS) method by which we can exactly identify the three parameters, α, δ, and β.[14] However, when subjects choose a corner point, $(X, 0)$ or $(0, Y)$, the allocation ratio $ln(\frac{x_t}{x_{t+k}})$ is not well-defined. To address this problem, we follow Andreoni et al. (2015) to estimate the parameters using an alternative representation of the first-order condition by the non-linear least squares (NLS) method:[15]

$$x_t = \frac{Y(\beta^{\mathbb{1}[t=0]}\delta^k P)^{-\frac{1}{\alpha}}}{1 + P(\beta^{\mathbb{1}[t=0]}\delta^k P)^{-\frac{1}{\alpha}}}. \quad (2)$$

3.2. The multiple price list (MPL) experiment

The second experiment is the MPL experiment of Andersen et al. (2008), which consists of two related experiments. The first stage is designed to provide information on the utility function curvature through a lottery choice MPL experiment of Holt and Laury (2002). The second stage is designed to identify time discounting parameters by a time preference MPL experiment.[16] As for delayed payments, we arranged in the same way as the CTB experiments explained above.

In this experiment, we also assume a time separable CRRA utility function: $U(x_t, x_{t+1}x_{t+2}, \dots) = \frac{x_t^{1-\tilde{\alpha}}}{1-\tilde{\alpha}} + \beta\sum_{k=1}^{\infty}\delta^k\frac{x_{t+k}^{1-\tilde{\alpha}}}{1-\tilde{\alpha}}$ where $\tilde{\alpha}$ represents the coefficient of the relative risk aversion.[17] As in the CTB experiment, the parameter δ captures the standard exponential discounting factor, and the parameter β denotes the quasi-hyperbolic discounting factor.

Specifically, in the first-stage Holt and Laury (2002)'s risk MPL experiment, subjects face a series of lottery choices, denoted by j, between a safe lottery, A, and a risky lottery, B. For each outcome of each lottery A and B, the probability $p(M_j^i)$, $i =$ A or B, is assigned to the two payoffs M_j^i by the experimenter. Thus, the expected utility for each lottery EU_i, $i =$ A or B; the ratio of expected utilities, ∇EU; and the conditional log-likelihood function can be defined as follows (Andersen et al., 2008):

$$EU_i = \sum_{j=1,2}(p(M_j^i) \times u(M_j^i)), \quad (3)$$

$$\nabla EU = \frac{EU_B^{\frac{1}{\mu}}}{EU_A^{\frac{1}{\mu}} + EU_B^{\frac{1}{\mu}}}, \quad (4)$$

$$lnL^{RA}(\tilde{\alpha}, \mu; A, B) = \sum_i(ln(\nabla EU|C_{Ri}=1) + ln(1-\nabla EU|C_{Ri}=0)), \quad (5)$$

where μ is a structural noise parameter, and C_{Ri} takes 1 when Lottery B is chosen and takes 0 when Lottery A is chosen.

In the second-stage time preference MPL experiment, individuals make a series of binary choices between smaller early payments X and larger delayed payments Y. Then, the present value of choosing the smaller early payments X, denoted by PV_X, in the multiple price list can be formalized as:

$$PV_X = \begin{cases} \frac{X^{1-\tilde{\alpha}}}{1-\tilde{\alpha}} & if\ t=0 \\ \beta\delta^t\frac{X^{1-\tilde{\alpha}}}{1-\tilde{\alpha}} & if\ t\neq 0 \end{cases} \quad (6)$$

The present value of choosing the larger delayed payment with delay lengths k, PV_Y, is

$$PV_Y = \begin{cases} \beta\delta^k\frac{Y^{1-\tilde{\alpha}}}{1-\tilde{\alpha}} & if\ t=0 \\ \beta\delta^{t+k}\frac{Y^{1-\tilde{\alpha}}}{1-\tilde{\alpha}} & if\ t\neq 0 \end{cases} \quad (7)$$

Then, an index of difference between these discounted values can be formed as follows.

$$\nabla PV = \frac{PV_Y^{\frac{1}{\nu}}}{PV_X^{\frac{1}{\nu}} + PV_Y^{\frac{1}{\nu}}}, \quad (8)$$

[13] The exact interest rates, experimental budgets, and delay lengths in the experiment in Japan and the Philippines are shown in Online Appendix.

[14] This equation clarifies the mapping from the variation of experimental parameters to structural parameter estimates. Variation in the gross interest rate, P, delivers the utility function curvature, α. For a fixed interest rate, variation in delay length, k, delivers, δ, and variation in whether the present, $t=0$, delivers β. Thus, these experimental variations allow us to estimate these three parameters via the delta method.

[15] This strategy allows us to estimate three parameters when $\alpha \in (0,1)$.

[16] The details about the Holt and Laury (2002) and time discount MPL experiments are described in the online appendix.

[17] With this functional form, $\tilde{\alpha}=0$ denotes the risk-neutral behavior, $\tilde{\alpha}>0$ denotes risk aversion, and $\tilde{\alpha}<0$ denotes risk tolerance.

where ν is a structural noise parameter. The conditional log-likelihood function is as follows.

$$lnL^{DR}(\beta,\delta,\tilde{\alpha};X,Y)=\sum_i(ln(\nabla PV|C_{Di}=1)+ln(1-\nabla PV|C_{Di}=0)). \tag{9}$$

where C_{Di} takes 1 when the delayed payment is chosen and takes 0 when an early payment is chosen. Following Andersen et al. (2008), we combine the two conditional log-likelihood functions (5) and (9) in the two stages to obtain the joint likelihood, which is a function of the coefficient of relative risk aversion ($\tilde{\alpha}$), hyperbolic and exponential discount rates (β and δ, respectively), and two noise parameters (ν and μ) as follows:

$$lnL(\beta,\delta,\tilde{\alpha},\nu,\mu;X,Y,A,B)=lnL^{DR}(\beta,\delta,\tilde{\alpha};X,Y)+lnL^{RA}(\tilde{\alpha},\mu;A,B). \tag{10}$$

4. Data and results I: The great East Japan earthquake

First, we check whether damages caused by the Great East Japan Earthquake were unpredictable and thus exogenous to households. Second, we use CTB data in 2014 and 2017 to examine whether the earthquake caused short-term- and long-term impacts on preferences. Finally, we employ the MPL data collected in 2017 to crosscheck the disaster impact on preference parameters.

4.1. Data and baseline covariate balance test

In Iwanuma city, local government conducted detailed metrical surveys of home damages and issued official damage certificates for each house, with which households could obtain government compensation and reallocation of donations. We collect officially-certified damage information from each of the respondents of the JAGES survey conducted in November 2013. House damages are divided into five categories depending on the extent of the damage: totally collapsed ($Zenkai$), almost collapsed ($Daikibo\ Hankai$), half collapsed ($Hankai$), minor damage ($Ichibu\ Sonkai$), or no damage ($Songai\ Nashi$). Based on these categories, we divide the sampled subjects with house damages into three groups. The first group includes subjects whose houses were not damaged. The second group includes subjects whose houses suffered minor or half damage. The third group includes subjects whose houses had almost or totally collapsed.

To check the exogeneity of damages, we regress each of the pre-disaster characteristics of the subjects on these three variables, depicting different damage levels with the no damage group as a reference category.[18] Based on the two methods of multiple hypothesis testing with multiple treatments, i.e., Romano-Wold and Westfall-Young tests, which are suitable for our data with three damage levels, we do not find systematic correlation between the damage level and each of the observed pre-disaster characteristics for subjects in either the 2014 or 2017 experiments (Table A.1).

In particular, we include a pre-disaster hyperbolic discounting measure collected from a retrospective survey in 2017: We follow Ikeda et al. (2010), Kang and Ikeda (2014, 2016) to capture each individual's timing of completing homework assignments during elementary school summer vacations and to construct a proxy variable of hyperbolic discounting, $Homework$, to capture each individual's timing for completing homework assignments during elementary and junior high school summer vacations. Elementary and junior high schools are compulsory in Japan. Since summer vacation is the longest holiday for students at that level, lasting around 40 days, most schools provide a substantial amount of homework for students during the long vacation. When to complete the homework depends on each student's self-control, and since it is not a pleasant task in most cases, we believe that it is the best measure to capture present bias or hyperbolic discounting during the respondents' adolescence. This variable, $Homework$, takes the value one if a subject completed homework assignments before the end of the summer vacation; and zero otherwise.

As shown in the last column of Table A.1 for the 2017 subjects, the pre-disaster hyperbolic discounting measure, $Homework$, and disaster exposure are uncorrelated. In addition, considering the causal impacts of hyperbolic discounting on harmful health behaviors such as over-eating, drinking, and smoking (Dupas, 2011; Story et al., 2014), we also use pre-disaster health behavior variables in baseline-balancing tests. The results are shown in columns (10), (11), and (12) of Table A.1 for 2014 and 2017 separately. We can verify that these health variables are not correlated with disaster exposure.

However, selection would threaten our causal identification of the impact of a disaster on preference parameters. According to Callen (2015), there are two problems in identifying the causal impacts of disasters on preference parameters with post-disaster data. The first is a "selective exposure" problem where individuals may be located according to their preferences before the disaster. Second, there may be a "selective migration" problem because individuals might selectively migrate out of affected zones based on their preferences in the wake of the disaster.

In Iwanuma data, dropouts mainly occur when a respondent passes away, enters a care facility, moves out of the city, or refuses to respond. Our data show that the migration rate is only 2.0–2.3%.[19] The lack of extensive migration may justify our empirical strategy that the earthquake provides a natural experimental situation to identify the causal effect of the disaster on households' preferences. However, the possibility remains that selection through exposure and migration would threaten our causal identification of the disaster impact on preference parameters. We carefully revisit this potential problem in Section 6.

[18] The data presents age and educational levels as of each interview date in November 2013.

[19] Out of 4568 valid respondents of the pre-disaster Iwanuma JAGES panel dataset in 2010, 577 participants had to be dropped out during the follow-up survey in 2013 because of death (434), moving out (92), loss of tracking information (17), and inability to participate owning to sickness (34).

Table 1
Aggregate and individual utility parameters estimated by the Convex Time Budget (CTB) experiments allowing for heterogeneity by damages in Japan (2014 and 2017).

Panel A: Aggregate analysis	(1)	(2)	(3)	(4)	(5)	(6)
		Experiments in 2014			Experiments in 2017	
Estimated parameters	β	δ	α	β	δ	α
No house damage	1.057	1.001	0.262	1.045	1.001	0.177
	(0.0366)	(0.00121)	(0.0289)	(0.0219)	(0.000738)	(0.0126)
Minor or half-damaged house	1.022	1.002	0.247	0.980	1.001	0.202
	(0.0226)	(0.000766)	(0.0178)	(0.0304)	(0.000773)	(0.0137)
Almost or totally-collapsed house	0.937	1.001	0.234	0.893	1.001	0.181
	(0.0432)	(0.00126)	(0.0248)	(0.0402)	(0.000871)	(0.0145)
Observations		4464			4296	
P-value of the null hypothesis for homogeneous parameters	0.0958	0.993	0.772	0.00290	0.721	0.381

Panel B: Individual analysis	(1)	(2)	(3)	(4)	(5)	(6)
		Experiments in 2014			Experiments in 2017	
Dependent variables	β	δ	α	β	δ	α
Minor or half-damaged house dummy	−0.0394	0.0307	−0.00249	−0.0162	0.0545	0.00626
	(0.0637)	(0.0974)	(0.00469)	(0.0554)	(0.0462)	(0.00433)
Almost or totally-collapsed house dummy	−0.167	0.0290	−0.00431	−0.146	−0.0211	−0.00153
	(0.0803)	(0.109)	(0.00509)	(0.0654)	(0.0471)	(0.00406)
Observations	186	186	186	179	179	179
P-value of the null hypothesis for homogeneous parameters	0.0997	0.933	0.698	0.0752	0.322	0.187

Notes: Individually clustered standard errors are reported in parentheses in panel A and robust standard errors are reported in parentheses in panel B. No House Damage is the group indicating subjects whose houses were not damaged. Minor or Half-damaged House is the group indicating that subjects whose houses suffered minor or half damage. Almost or Totally-collapsed House is the group indicating subjects whose houses almost or totally collapsed. The CTB experiment of Andreoni et al. (2015) allows us to separately identify the three key parameters of the time-separable CRRA utility function with the β-δ discounting (Strotz, 1955; Phelps and Pollak, 1968; Laibson, 1997)—the quasi-hyperbolic discounting factor showing present bias, β; the exponential time discounting factor, δ; and the degree of intertemporal elasticity of substitution, α.

4.2. The CTB experiment results

We estimate the model of Eq. (1) by allowing a heterogeneous degree of intertemporal rate of substitution, α; exponential time discounting factor, δ; and quasi hyperbolic discounting factor, β, depending on each of the three house-damage categories.[20] We also estimate β, δ and α at the individual level and examine the disaster impact on each of the estimated parameters. The results are shown in Table 1. While the estimated β exceeds one, suggesting the existence of overall future bias, it is not necessarily inconsistent with other findings in the existing literature. According to Andreoni and Sprenger (2012), Andreoni et al. (2015), the present bias parameters, β, estimated by the CTB experiments with monetary rewards are 1.004 and 1.010, respectively. Abdellaoui et al. (2010) proposes another experimental framework with monetary incentives and shows that the median of β is 0.99. The estimated β reported by Augenblick et al. (2015) exploiting real-effort choices is 0.89. DellaVigna and Pope (2018) combines monetary and non-monetary incentives and finds that the estimated β is 1.17.

According to Table 1, as house damages become more severe, the estimated β becomes systematically lower. In fact, when we compare the status "No House Damage" with "Almost or Totally-collapsed House" caused by the disaster, β decreases by 0.120 from 1.057 to 0.937 in 2014 (column (1)) and 0.152 from 1.045 to 0.893 in 2017 (column (4)) at the aggregate level, and by 0.167 in 2014 (column (1)) and by 0.146 in 2017 (column (4)) at the individual level. We reject the null hypothesis that the parameters, β, are the same, irrespective of house damages in both years. In contrast, we do not observe the earthquake's impacts on other parameters, that is, α and δ at aggregate and individual levels. These findings indicate that while moderate exposure to house damages caused by the Great East Japan Earthquake in 2011 seems to fix future bias towards exponential discounting, extreme exposure seems to make people present-biased consistently in both 2014 and 2017. The pooled and balanced panel data confirm the finding that the disaster's effect persisted for at least 6 years.[21]

[20] In Appendix Table A.2 shows the aggregate estimation results of homogeneous parameters by data from subjects who participated in 2014 and 2017, respectively. In these two tables, the first two columns report the estimated parameter based on Eq. (3) using OLS and the last column shows results based on Eq. (4) using NLS. There are several differences between the results in 2014 and those in 2017. First, in all specifications of Appendix Table A.2, we cannot reject the null hypothesis in which the present bias parameter, β, equals to one in the 2014 data. Second, both results in 2014 and 2017 show that the exponential time discounting parameter, δ, is within a reasonable range. Finally, the degree of intertemporal substitution parameter, α, in 2014 and 2017, ranges from 0.08 and 0.25.

[21] These results are shown in Online Appendix (Table A.3).

Table 2
Utility parameters estimated by the Multiple Price List (MPL) experiments allowing for heterogeneity by damages in Japan (2017).

Estimated parameters	δ	ν	β	$\tilde{\alpha}$	μ
No house damage	0.999	0.0585	1.015	0.634	0.349
	(0.000276)	(0.0195)	(0.0111)	(0.0773)	(0.0778)
Minor or half-damaged house	0.999	0.128	0.999	0.422	0.327
	(0.000291)	(0.0251)	(0.0156)	(0.0617)	(0.0410)
Almost or totally-collapsed house	0.999	0.131	0.930	0.292	0.395
	(0.000563)	(0.0298)	(0.0352)	(0.0897)	(0.0751)
Observations			25776		
P-value of the null hypothesis for homogeneous parameters	0.459	0.0349	0.0632	0.0113	0.727

Notes: Individually clustered standard errors are reported in parentheses. No House Damage is the group indicating subjects whose houses were not damaged. Minor or Half-damaged House is the group indicating that subjects whose houses suffered minor or half damage. Almost or Totally-collapsed House is the group indicating subjects whose houses almost or totally collapsed. The MPL experiment of Andersen et al. (2008) consists of two MPL experiments. The first stage is designed to provide information on the utility function curvature through a lottery choice MPL experiment of Holt and Laury (2002). The second stage is designed to identify time discounting parameters by a time preference MPL experiment. This experiment allows us to separately identify the three key parameters of the time-separable CRRA utility function with the β-δ discounting (Strotz, 1955; Phelps and Pollak, 1968; Laibson, 1997)—the quasi-hyperbolic discounting factor showing present bias, β; the exponential time discounting factor, δ; and $\tilde{\alpha}$ the coefficient of the relative risk aversion with two noise parameters, ν and μ.

4.3. The MPL experiment results

With experimental data in 2017, we also estimate the MPL model by allowing heterogeneous parameters, depending on the degree of the house damage (Table 2).[22] We find that house damages make people fix future bias towards exponential discounting or present bias. With undamaged houses, the present bias parameter, β, is 1.015; with minor or half damages, the present bias parameter is 0.999; and, with almost totally or totally collapsed house, the estimated β decreases further to 0.930. A joint test also confirms this pattern. However, the disaster impact on β is smaller with the MPL method than that observed with the CTB method. Part of the decline in β may be absorbed by a change in the curvature, $\tilde{\alpha}$, in the case of MPL—the risk aversion parameter, $\tilde{\alpha}$, drops from 0.634 to 0.292 with an increase in the damage level, indicating that disaster damages make people less risk averse.

We can graphically show these results. In Figs. 2 and 3 which show the relationship between gross interest rates and proportion of subjects choosing sooner payments, we compare the case $\{t = 0, k = 35\}$ or $\{t = 0, k = 63\}$ with the one where $\{t = 35, k = 35\}$ or $\{t = 63, k = 63\}$. While the choice between today and a future date is systematically related to damages, the choice between two points in the future are not necessarily sensitive to damages. We clearly observe that the extreme disaster damage makes people present-biased.

As for the disaster impact on risk attitudes, we present (Holt and Laury, 2002) experiment results allowing heterogeneity across degree of damages. According to Fig. 4, those who suffered house damage are less likely to choose the safer lottery even when the probability of winning the larger prize is close to zero. This figure indicates that individuals with larger house damages show less risk aversion.

5. Data and results II: The Habagat Spawned floods in the Philippines

We also undertake the following three procedures using the Philippines data. First, we check the exogeneity of the damage caused by the floods induced by "Habagat". Subsequently, we employ the CTB data to estimate present bias, exponential discounting, and the intertemporal elasticity of substitution. Finally, we also use MPL data to obtain estimates of present bias, exponential discounting, and the relative risk-aversion parameters.

5.1. Data and baseline covariate balance test

The flood's damage levels are captured objectively and subjectively. Concerning the objective damage information, we employ the satellite imageries, which identify whether households suffered farm-level damages due to the submergence of paddy fields by the flood (i.e., the overflow of the lake water). By comparing two 5 km by 5 km images taken by IKONOS before (May 23, 2012) and after (August 11, 2012) the floods, we can identify the flood border shown by the red line of Fig. 5 .[23] Since the ground level geographic information systems (GIS) data on landownership data can be matched with the satellite image only in the East Laguna Village, but not the two surrounding villages, we could obtain 99 and 91 observations, respectively, in 2014 and 2017.

[22] The estimation results using the MPL and Holt and Laury (2002) are shown in the Online Appendix. Table A.4 shows estimation results of the three parameters together with the error parameters using the MPL experiment conducted only in 2017. The estimated present bias parameter, β, is 0.994, and hence we cannot statistically reject the null hypothesis that β equals to one. The estimated risk aversion parameter, $\tilde{\alpha}$, is 0.443. Since the estimated intertemporal elasticity of substitution, α, by CTB, ranges from 0.144 to 0.247 in 2014 and from 0.082 to 0.189 in 2017 (Table A.2), the estimated intertemporal elasticity, $\tilde{\alpha}$, by MPL, and the relative risk-aversion coefficient, $\tilde{\alpha}$, by MPL, are quite different, rejecting the expected utility framework. We also find that the two noise parameters are not substantial, suggesting that subjects made theoretically consistent decisions—noise parameter in the MPL experiment, ν, is 0.109, and noise parameter in the (Holt and Laury, 2002) experiment, μ, is 0.359.

[23] In Fig. 5, we overlay the post-flood satellite image with the flood border in red on self-reported flood water depth with five categories in blue: lightest blue (below ankle depth < 10 cm), light blue (below knee depth < 40 cm), blue (below hip depth < 80 cm), dark blue (below chest depth < 120 cm), and darkest blue (above chest depth > 120 cm). These two pieces of information seem to be consistent.

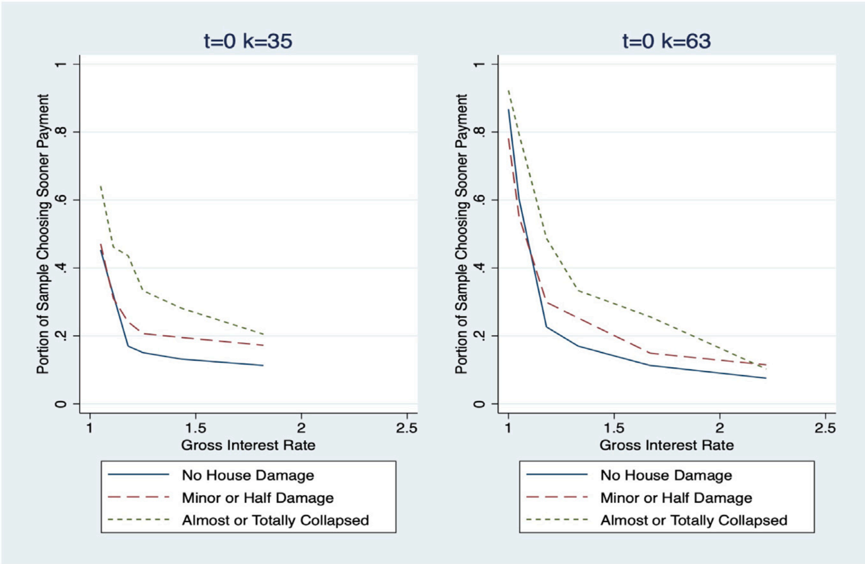

Fig. 2. Summary of MPL data by house damage status in Japan (2017).
Notes: Fig. 2 shows the relationship between gross interest rates and proportion of subjects choosing sooner payments in the cases $\{t = 0, k = 35\}$ and $\{t = 0, k = 63\}$. In the Multiple Price List (MPL) experiments, individuals make a series of binary choices between smaller early payments and larger delayed payments involving combinations of starting times, t; delay lengths, k; and annual interest rates.

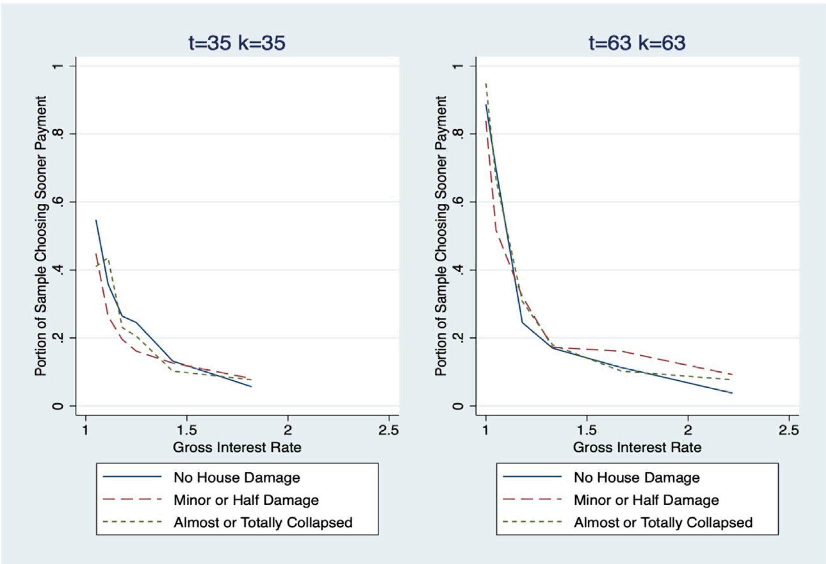

Fig. 3. Summary of MPL data by house damage status in Japan (2017).
Notes: Fig. 3 shows the relationship between gross interest rates and proportion of subjects choosing sooner payments in the cases $\{t = 35, k = 35\}$ and $\{t = 63, k = 63\}$. In the Multiple Price List (MPL) experiments, individuals make a series of binary choices between smaller early payments and larger delayed payments involving combinations of starting times, t; delay lengths, k; and annual interest rates.

Concerning the subjective damage levels, we construct a disaster damage variable from self-reported damage information, including home damage, farm damage, asset damage, income decline, debt increase, and injury and/or sickness, available for all three villages.

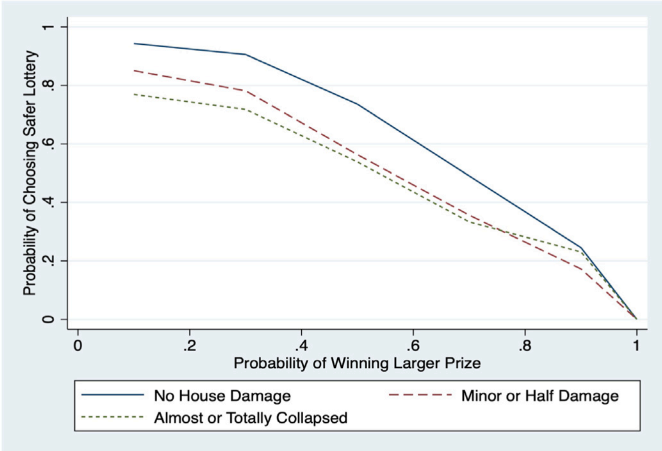

Fig. 4. Summary of holt and laury data by house damage status in Japan (2017).
Notes: Fig. 4 shows the relationship between the probability of winning a larger prize and the probability of choosing a safer lottery. In the first-stage Holt and Laury (2002)'s risk MPL experiment, subjects face a series of lottery choices between a safe lottery and a risky lottery.

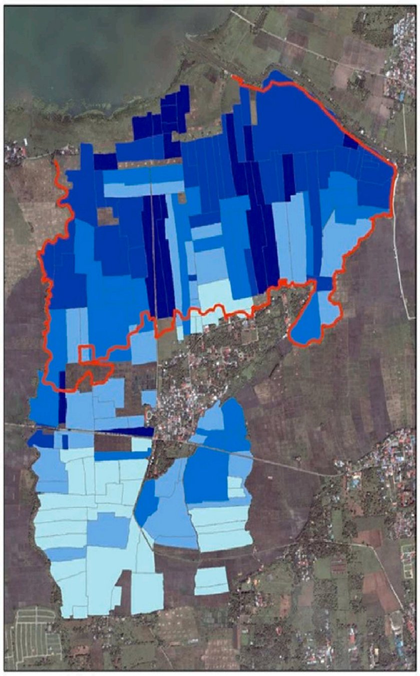

Fig. 5. The satellite image of farms.
Notes: The data on self-reported water depth is overlaid on the satellite image with five categories: lightest blue (below ankle depth <10 cm), light blue (below knee depth <40 cm), blue (below hip depth <80 cm), dark blue (below chest depth <120 cm), and darkest blue (above chest depth >120 cm). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Accordingly, we define a damage variable combining objective and subjective information, "Flood Damage", which is an indicator variable based on the subjective and objective reports, which takes one when households suffered from at least three kinds of damages, out of the satellite-based objective farm damage and the five self-reported subjective damages except for the subjective farm damage.

Based on this damage variable, we perform a covariate balance test by regressing each of the following observed pre-disaster characteristics of subjects before the floods (i.e., household size, indicator variable of head's sex, head's age, head's years of

Table 3
Aggregate and individual utility parameters estimated by the Convex Time Budget (CTB) experiments allowing for heterogeneity by damages in the Philippines (2014 and 2018).

Panel A: Aggregate analysis	(1)	(2)	(3)	(4)	(5)	(6)
		Experiments in 2014			Experiments in 2018	
Estimated parameters	β	δ	α	β	δ	α
No flood damage	0.864	0.993	0.130	0.903	0.995	0.120
	(0.0247)	(0.000811)	(0.0138)	(0.0359)	(0.000836)	(0.0123)
Flood damage	0.703	0.995	0.164	0.746	0.994	0.123
	(0.0628)	(0.00159)	(0.0284)	(0.0423)	(0.00114)	(0.0166)
Observations		2352			2184	
P-value of the null hypothesis for homogeneous parameters	0.0165	0.348	0.282	0.0047	0.806	0.897

Panel B: Individual analysis	(1)	(2)	(3)	(4)	(5)	(6)
		Experiments in 2014			Experiments in 2018	
Dependent variables	β	δ	α	β	δ	α
Flood damage dummy	−0.210	0.00455	−0.164	−0.328	−0.0164	−0.441
	(0.0915)	(0.0144)	(0.299)	(0.104)	(0.0204)	(0.444)
Observations	98	98	98	91	91	91

Notes: Individually clustered standard errors are reported in parentheses in panel A and robust standard errors are reported in parentheses in panel B. No Flood Damage is the group indicating subjects whose households experienced less than three kinds of damages, including farm damage, as identified by the satellite image. Flood Damage is the group indicating subjects whose households experienced at least three kinds of damages, including farm damage, as identified by the satellite image. The CTB experiment of Andreoni et al. (2015) allows us to separately identify the three key parameters of the time-separable CRRA utility function with the β-δ discounting (Strotz, 1955; Phelps and Pollak, 1968; Laibson, 1997)—the quasi-hyperbolic discounting factor showing present bias, β; the exponential time discounting factor, δ; and the degree of intertemporal elasticity of substitution, α.

Table 4
Utility parameters estimated by the Multiple Price List (MPL) experiments allowing for heterogeneity by damages in the Philippines (2014 and 2018).

Estimated parameters	Experiments in 2014				
	δ	ν	β	$\tilde{\alpha}$	μ
No flood damage	0.996	0.150	0.960	0.554	0.208
	(0.00133)	(0.0475)	(0.0245)	(0.130)	(0.0641)
Flood damage	0.993	0.303	0.762	0.199	0.302
	(0.00231)	(0.103)	(0.0823)	(0.214)	(0.0856)
Observations	14112				
P-value of the null hypothesis for homogeneous parameters	0.250	0.177	0.0209	0.156	0.382

Estimated parameters	Experiments in 2018				
	δ	ν	β	$\tilde{\alpha}$	μ
No flood damage	0.998	0.0920	0.945	0.632	0.162
	(0.000818)	(0.0355)	(0.0226)	(0.131)	(0.0576)
Flood damage	0.998	0.0995	0.823	0.552	0.196
	(0.000857)	(0.0421)	(0.0701)	(0.174)	(0.0769)
Observations	13104				
P-value of the null hypothesis for homogeneous parameters	0.742	0.892	0.0978	0.714	0.729

Notes: Individually clustered standard errors are reported in parentheses. No Flood Damage is the group indicating subjects whose households experienced less than three kinds of damages, including farm damage, as identified by the satellite image. Flood Damage is the group indicating subjects whose households experienced at least three kinds of damages, including farm damage, as identified by the satellite image. The MPL experiment of Andersen et al. (2008) consists of two MPL experiments. The first stage is designed to provide information on the utility function curvature through a lottery choice MPL experiment of Holt and Laury (2002). The second stage is designed to identify time discounting parameters by a time preference MPL experiment. This experiment allows us to separately identify the three key parameters of the time-separable CRRA utility function with the β-δ discounting (Strotz, 1955; Phelps and Pollak, 1968; Laibson, 1997)—the quasi-hyperbolic discounting factor showing present bias, β; the exponential time discounting factor, δ; and $\tilde{\alpha}$ the coefficient of the relative risk aversion with two noise parameters, ν and μ.

education, married dummy, widow dummy, the proportion of food consumption out of the total monthly consumption before the floods, and the amount of cash loans taken before the floods) on the damage variable.[24] With either 2014 or 2018 data, the Romano-Wold and Westfall-Young tests of multiple hypothesis show that each of the pre-disaster household characteristics is uncorrelated with the damage level (Tables A.5 and A.6).[25]

As for the selective migration issue, according to the complete lists of farmers in 2007 and 2013 which are available from the previous surveys conducted by IRRI, we verify that no one migrated out between the timing of Habagat in 2012 and the IRRI survey in 2013. While we believe that the issue of selective migration is not a major concern in the Philippines, we will revisit the potential problem carefully in Section 6.

5.2. The CTB experiment results

In order to examine the impact of the floods, we estimate the model by allowing the heterogeneous curvature parameter, α; exponential time discounting parameter, δ; and the present bias parameter, β, depending on the damage category we defined, "Flood Damage".[26] We also estimate β, δ and α at the individual level and examine the damage impact on each of the estimated parameters. The estimation results in Table 3 show that when we compare the status "No Flood Damage" with "Flood Damage" caused by the flood, β decreases substantially, suggesting that exposure to the disaster seems to reinforce people's present bias. In contrast, other parameters, α and δ, are largely unaffected by the disaster.

5.3. The MPL experiment results

We also employ MPL experiment data from the Philippines in 2014 and 2018 to estimate the impact of the floods on preference parameters. Tables 4 for 2014 and 2018, respectively, show the estimation results, wherein the estimated quasi-hyperbolic discounting factor, β, is consistently smaller for those who were exposed to the floods than those who were unaffected with reasonable level of statistical significance. Qualitatively, these results may be seen as being comparable to the ones we obtain from the Japanese data.[27]

6. Possibility of selection

As we discussed, selective exposure and migration would threaten our causal identification of the disaster impact on preference parameters (Callen, 2015). Our baseline balancing test results, both in Iwanuma and the Philippines, show the non-existence of systematic correlation between the damage level and each of the observed pre-disaster characteristics. Yet, there still is a concern for selective exposure and selective migration.[28] To handle this concern, we follow Oster (2019) and quantify omitted variable bias arising from endogenous migration. According to Oster (2019), the inclusion of observed controls allows us to infer the bias from the unobservables and to calculate bounds on the disaster effect. In our specification, we control for sex, age and smoking dummy variables. Among these variables, the smoking dummy variable is a proxy for time and risk preferences (Kan, 2007; Anderson and Mellor, 2008; Dupas, 2011; Story et al., 2014). Thus, we believe that the inclusion of the smoking dummy variable captures omitted variable bias at least partially and derives bounds for the causal impact of the disaster. The estimation results are reported in Table 5. Our bound estimates are similar to the ones reported in Table 1 and we only observe the statistically significant bound corresponding to the effect of the disaster on the present bias. Hence, we believe our results are unlikely to be driven by selective exposure and migration bias.

Yet, there is a possibility that our estimate might be different from the effect of a disaster on a sample of the (pre-disaster) exposed population. To strengthen our argument, we use the key observables as weights and run the weighted regression, where we employ the following weights interchangeably: age, sex, education and smoking dummy for Japan; and household size, head's sex, head's age and head's years of schooling for the Philippines. In Japan, we make the sample representative of the non-migrants in 2010, i.e. "stayers" of the population, as well as the entire population from 2010. In the Philippines, we make the sample representative of the exposed population in the East Laguna village as of 2012. The estimation results are reported in Tables 6 and 7 for Japan and

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[24] These data were collected before the floods in August 2012, except for the age information, which is as of each experiment date in March 2014.

[25] The covariate balance test may seem underpowered with less than 100 observations. To check the power empirically, we regress the individually estimated post-disaster present-bias β on the damage status. The result shows overall statistically significance which supports that the sample size is enough to perform the covariate balance test.

[26] Table A.7 shows the estimation results of three parameters using the CTB experiment data from the Philippines. In all specifications, the estimated present bias parameter, β, falls below one and is smaller than the estimated β in Japan. This result suggests that subjects in developing countries show substantial quasi-hyperbolic discounting. The estimated exponential time discounting and intertemporal elasticity of substitution parameters are within reasonable ranges.

[27] Table A.8 shows estimation results of the three parameters, together with error parameters, derived using the MPL experiment data. Subjects also show their present biasedness in MPL—the present bias parameters, β, are 0.880 in 2014 and 0.913 in 2018, and we statistically reject the null hypothesis that β equals to one. The estimated risk aversion parameters, $\tilde{\alpha}$, are 0.32 in 2014 and 0.533 in 2018, which are plausibly consistent with the existing studies. However, these risk aversion coefficients deviate from the estimated intertemporal elasticity of substitution, α, particularly in 2014, using the CTB experiment, that is, 0.147–0.282 in 2014 and 0.124–0.241 in 2018.

[28] Mironova et al. (2019) examines risk tolerance among rebel combatants and civilians in Syria and identifies a sorting mechanism during conflict where risk averse individuals select out of conflict.

Table 5
Individual utility parameters estimated by the Convex Time Budget (CTB) experiments allowing for heterogeneity by damages in Japan (2014 and 2017): Bound approach.

Dependent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Experiments in 2014						Experiments in 2017					
	β	β	δ	δ	α	α	β	β	δ	δ	α	α
Minor or half-damaged house dummy	−0.0405		−0.00235		0.0605		−0.0332		0.00722		0.0705	
	(0.0957)		(0.00671)		(0.124)		(0.0758)		(0.00813)		(0.0749)	
Almost or totally-collapsed house dummy		−0.197		−0.00498		0.0825		−0.158		−0.000788		−0.0124
		(0.0712)		(0.00751)		(0.143)		(0.0718)		(0.00737)		(0.0732)
Observations	186	186	186	186	186	186	179	179	179	179	179	179

Notes: We follow Oster (2019) to calculate bounding values for unbiased coefficients. Bootstrap standard errors are reported in parentheses. We control for sex, age and smoking dummy and set the maximal R^2 to 1.3 times the R^2 of each regression. Minor or Half-damaged House is the group indicating that subjects whose houses suffered minor or half damage. Almost or Totally-collapsed House is the group indicating subjects whose houses almost or totally collapsed.

the Philippines, respectively. The results show that exposure to the disaster reinforces only present bias of the exposed population both in Japan and the Philippines.

Moreover, individuals who agreed to participate in our experiments may be systematically different from the rest of the population. When the probability of an individual's participation in experiments is correlated with the outcomes of the experiments, there will be site selection bias in estimating the impacts of disasters (Allcott, 2015; Banerjee et al., 2017). To check and handle the existence of such a bias, we employ the following control function approach to the JAGES census data from Iwanuma city. In this approach, we estimate the probability of participation in the experiments jointly with the main Euler equation for the CTB experiments, that is, Eq. (1), using a two-step estimation method under the joint normality assumption with bootstrapped standard errors. To estimate the probability of controlling for sample selection bias, we include the smoking dummy variable, a proxy measure of pre-disaster time and risk preferences, as an independent variable. Then, we regress each of the estimated individual preference parameters on the damage variables, covariates, and selection correction term derived from the first-stage equation.

Table 8 presents the estimation results for the second-stage model. The coefficients of the selection correction term derived from the first-stage equation are mostly statistically significant, indicating nonrandom selection. Importantly, the qualitative results for both the 2014 and 2017 experimental data are maintained, even after correcting for potential site-selection bias. These results suggest that such bias is not necessarily serious in our setting.

7. Discussion

7.1. Possible time trajectory

One might think our results on time discounting in Japan and the Philippines differ from those of Callen (2015) which examines the impact of the Indian Ocean Earthquake tsunami in Sri Lanka: While Callen (2015) finds that exposure to the disaster has a positive effect on the time discount factor after two and a half years, our study shows no effect of the tsunami and floods on the exponential discount factor, δ. However, our individual analyses for Japan (Table 1, Panel B) and the Philippines (Table 3, Panel B) show that the effect on the discount factor, δ, is positive in the first wave of experiments after three and two years, respectively, but mainly negative in the second wave of experiments after six years, although neither is statistically significant. These findings, along with those of Callen (2015), suggest that the effect is positive in the short-term and diminishes over time. Indeed, the following two existing studies seem to be consistent with this conjecture: While Chantarat et al. (2019) finds that victims of the 2011 mega flood in Cambodia show higher patience after three years, Cassar et al. (2017) reports that Thai people who experienced the December 2004 Indian Ocean tsunami appear to discount the future more four and a half years after the disaster. However, it should be noted that this explanation is speculative, and further careful investigations are needed to address this issue in the future.

7.2. Potential frameworks

Why do disasters make people "seemingly" more present-biased in the short and long-term periods? To address this question, we follow existing studies to consider two possible frameworks for the nexus between disaster exposure and present bias: Callen et al. (2014), Callen (2015).

First, Callen et al. (2014) finds a relationship between trauma and a preference for certainty. Callen et al. (2014) demonstrates that fearful recollections trigger an increased preference for certainty among individuals exposed to violence.[29] We predict that the exacerbated certainty effect caused by traumatic exposure would make individuals more present-biased. To investigate this potential channel empirically, we analyze whether the exposed individuals in Japan show psychological responses.

In the JAGES data from Japan, we employ questions on three binary variables taken from the clinically-validated $K6$ depression measure of Kessler et al. (2002): First, "Desperate Feeling" takes 1 when the respondents feel that their lives are desperate and 0

[29] An intuition behind this finding is provided by Lerner and Keltner (2001), who explains that the sense of uncertainty and lack of control associated with fear should lead fearful individuals to make certainly enhancing choices.

Table 6
Individual utility parameters estimated by the Convex Time Budget (CTB) experiments allowing for heterogeneity by damages in Japan (2014 and 2017): Weighted approach.

(A) Weight variable: Stayer

Experiments in 2014	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variables	β	δ	α	β	δ	α	β	δ	α	β	δ	α
Minor or half-damaged house dummy	−0.0139	−0.00229	0.0398	−0.0423	−0.00263	0.0312	−0.0415	−0.00260	0.0200	−0.0405	−0.00248	0.0298
	(0.0733)	(0.00481)	(0.104)	(0.0640)	(0.00471)	(0.0988)	(0.0677)	(0.00505)	(0.0939)	(0.0639)	(0.00471)	(0.0973)
Almost or totally-collapsed house dummy	−0.147	−0.00628	0.00212	−0.169	−0.00446	0.0261	−0.182	−0.00532	−0.0234	−0.171	−0.00435	0.0308
	(0.0825)	(0.00473)	(0.102)	(0.0803)	(0.00506)	(0.107)	(0.0826)	(0.00500)	(0.0970)	(0.0806)	(0.00511)	(0.111)
Observations	186	186	186	186	186	186	186	186	186	186	186	186
P-value of the null hypothesis for homogeneous parameters	0.0989	0.373	0.924	0.0956	0.678	0.937	0.0696	0.547	0.927	0.0922	0.696	0.932
Weight Variable	Age	Age	Age	Sex	Sex	Sex	Education	Education	Education	Smoking	Smoking	Smoking

Experiments in 2017	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variables	β	δ	α	β	δ	α	β	δ	α	β	δ	α
Minor or half-damaged house dummy	−0.0269	0.00457	0.0438	−0.00835	0.00668	0.0643	−0.00783	0.00653	0.0621	−0.00642	0.00700	0.0619
	(0.0541)	(0.00397)	(0.0426)	(0.0572)	(0.00445)	(0.0468)	(0.0639)	(0.00494)	(0.0513)	(0.0559)	(0.00441)	(0.0467)
Almost or totally-collapsed house dummy	−0.137	−0.00173	−0.0205	−0.149	−0.00216	−0.0302	−0.136	−0.00133	−0.0100	−0.150	−0.00147	−0.0200
	(0.0627)	(0.00390)	(0.0447)	(0.0653)	(0.00395)	(0.0474)	(0.0750)	(0.00539)	(0.0561)	(0.0660)	(0.00404)	(0.0467)
Observations	178	178	178	179	179	179	179	179	179	179	179	179
P-value of the null hypothesis for homogeneous parameters	0.0915	0.326	0.406	0.0615	0.118	0.183	0.152	0.277	0.375	0.0620	0.147	0.264
Weight variable	Age	Age	Age	Sex	Sex	Sex	Education	Education	Education	Smoking	Smoking	Smoking

(B) Weight variable: Total

Experiments in 2014	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variables	β	δ	α	β	δ	α	β	δ	α	β	δ	α
Minor or half-damaged house dummy	−0.00796	−0.00356	0.0539	−0.0419	−0.00261	0.0311	−0.0385	−0.00244	0.0351	−0.0395	−0.00249	0.0306
	(0.0834)	(0.00478)	(0.133)	(0.0639)	(0.00470)	(0.0986)	(0.0638)	(0.00468)	(0.1000)	(0.0637)	(0.00470)	(0.0974)
Almost or totally-collapsed house dummy	−0.118	−0.00612	0.0268	−0.169	−0.00444	0.0265	−0.161	−0.00388	0.0534	−0.168	−0.00432	0.0292
	(0.0914)	(0.00465)	(0.109)	(0.0803)	(0.00506)	(0.107)	(0.0820)	(0.00527)	(0.116)	(0.0803)	(0.00509)	(0.109)
Observations	186	186	186	186	186	186	186	186	186	186	186	186
P-value of the null hypothesis for homogeneous parameters	0.251	0.422	0.913	0.0961	0.681	0.936	0.133	0.758	0.869	0.0988	0.698	0.933
Weight variable	Age	Age	Age	Sex	Sex	Sex	Education	Education	Education	Smoking	Smoking	Smoking

Experiments in 2017	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variables	β	δ	α	β	δ	α	β	δ	α	β	δ	α
Minor or half-damaged house dummy	−0.0269	0.00457	0.0438	−0.00859	0.00667	0.0640	−0.0179	0.00621	0.0529	−0.00917	0.00679	0.0598
	(0.0541)	(0.00397)	(0.0426)	(0.0571)	(0.00445)	(0.0467)	(0.0548)	(0.00430)	(0.0460)	(0.0558)	(0.00438)	(0.0466)
Almost or totally-collapsed house dummy	−0.137	−0.00173	−0.0205	−0.149	−0.00214	−0.0299	−0.148	−0.00158	−0.0239	−0.148	−0.00149	−0.0203
	(0.0627)	(0.00390)	(0.0447)	(0.0653)	(0.00396)	(0.0474)	(0.0649)	(0.00389)	(0.0464)	(0.0658)	(0.00404)	(0.0468)
Observations	178	178	178	179	179	179	179	179	179	179	179	179
P-value of the null hypothesis for homogeneous parameters	0.0915	0.326	0.406	0.0619	0.120	0.186	0.0683	0.177	0.316	0.0655	0.157	0.280
Weight variable	Age	Age	Age	Sex	Sex	Sex	Education	Education	Education	Smoking	Smoking	Smoking

Notes: Robust standard errors in parentheses. Minor or Half-damaged House is the group indicating that subjects whose houses suffered minor or half damage. Almost or Totally-collapsed House is the group indicating subjects whose houses had almost or totally collapsed. Age refers to the age of the participants. Sex is equal to 1 for male participants. Education takes 1 for participants with complete compulsory education and 0 otherwise. Smoking" takes 1 when they smoke sometimes or almost every day and 0 otherwise.

Table 7
Individual utility parameters estimated by the Convex Time Budget (CTB) experiments allowing for heterogeneity by damages in the Philippines (2014 and 2018): Weighted approach.

Weight variable: Total

Dependent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Experiments in 2014											
	β	δ	α	β	δ	α	β	δ	α	β	δ	α
Flood damage dummy	−0.218	0.00221	−0.190	−0.205	0.00461	−0.171	−0.255	−0.00771	−0.279	−0.216	0.00692	−0.117
	(0.0920)	(0.0152)	(0.318)	(0.0921)	(0.0148)	(0.306)	(0.121)	(0.0245)	(0.490)	(0.0904)	(0.0134)	(0.277)
Observations	96	96	96	98	98	98	98	98	98	98	98	98
Weight variable	Household Number	Household Number	Household Number	Head Sex	Head Sex	Head Sex	Head Age	Head Age	Head Age	Head years of Schooling	Head Years of Schooling	Head Years of Schooling

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Experiments in 2018											
Dependent variables	β	δ	α	β	δ	α	β	δ	α	β	δ	α
Flood damage dummy	−0.327	−0.0123	−0.310	−0.334	−0.0176	−0.430	−0.248	−0.00273	−0.167	−0.332	−0.0198	−0.339
	(0.107)	(0.0195)	(0.445)	(0.107)	(0.0213)	(0.455)	(0.140)	(0.0229)	(0.486)	(0.105)	(0.0231)	(0.512)
Observations	89	89	89	91	91	91	91	91	91	91	91	91
Weight variable	Household Number	Household Number	Household Number	Head Sex	Head Sex	Head Sex	Head Age	Head Age	Head Age	Head years of Schooling	Head years of Schooling	Head years of Schooling

Notes: Robust standard errors are reported in parentheses. Flood Damage is the group indicating subjects whose households experienced at least three kinds of damages, including farm damage, as identified by the satellite image. Household Number is the number of household members. Head Age is age of the head. Head Sex is equal to 1 when their head is male. Head Years of Schooling is years of schooling of the head.

Table 8
Individual utility parameters estimated by the Convex Time Budget (CTB) experiments allowing for heterogeneity by damages and sample selection in Japan (2014 and 2017).

Individual Analysis	(1)	(2)	(3)	(4)	(5)	(6)
	Experiments in 2014			Experiments in 2017		
Dependent variables	β	δ	α	β	δ	α
Minor or half-damaged house	−0.0523	0.00524	−0.227	−0.0202	0.00542	0.0118
	(0.0671)	(0.00823)	(0.173)	(0.0495)	(0.00451)	(0.0695)
Almost or totally-collapsed house	−0.184	−0.00664	−0.0465	−0.149	−0.00159	0.0321
	(0.0791)	(0.00566)	(0.148)	(0.0677)	(0.00513)	(0.0615)
Sample selection	−0.0971	0.0323	−1.287	0.395	0.0393	−0.516
	(0.226)	(0.0182)	(1.118)	(0.219)	(0.0195)	(0.193)
Observations	6422	6422	6422	6423	6423	6423
P-value of the null hypothesis: All of the three are the same	0.0467	0.386	0.418	0.0779	0.276	0.872

Notes: Bootstrap standard errors in parentheses. No House Damage is the group indicating subjects whose houses were not damaged. Minor or Half-damaged House is the group indicating that subjects whose houses suffered minor or half damage. Almost or Totally-collapsed House is the group indicating subjects whose houses had almost or totally collapsed. The CTB experiment of Andreoni et al. (2015) allows us to separately identify the three key parameters of the time-separable CRRA utility function with the β-δ discounting (Strotz, 1955; Phelps and Pollak, 1968; Laibson, 1997)—the quasi-hyperbolic discounting factor showing present bias, β; the exponential time discounting factor, δ; and the degree of intertemporal elasticity of substitution, α. We employ age, age-squared, job dummy, earthquake insurance subscription dummy and smoking dummy as covariates in the first-stage sample selection equation and age, age-squared, job dummy, and earthquake insurance subscription dummy for covariates in the second-stage equation. "Sample Selection" reports the coefficient on the sample selection correction term derived from the first-stage selection equation to correct for the sample selection.

otherwise; second, "Hopeless Life" takes 1 when they feel that their lives are hopeless and 0 otherwise; and third, "Something Bad" takes 1 when they feel something bad will happen in the future and 0 otherwise. We regress each of these three binary variables on the house damage variables. Table 9 presents the estimated results for the years 2014 and 2017. These results suggest that disaster exposure seems to make subjects feel more "Desperate" and "Hopeless" persistently even after six years, arguably supporting the proposed psychological framework.

There are potential concerns about selection examined in Section 6 because we exploit the differences in disaster exposure that may trigger migration. To validate our analysis, we follow the bound and weighted regression approaches as before. The results are presented in Tables 10 and 11. Since our estimates are comparable to those reported in Table 9, we believe that our results are robust and unlikely to be driven by selection bias.

Second, Callen (2015) proposes another framework to characterize the three potential channels through which disaster exposure could affect individuals' patience: subjective expectations about the future; changes in consumption levels due to economics losses; and changes in taste. We empirically test the first channel through which a disaster decreases subjective expectations about the future in the Philippines, leading to less patience and increased consumption from the future to the present.

During the 2018 experiments in the Philippines, we asked whether the subjects perceived a decline in their life expectancy after the 2012 flood. According to the result reported in Table 12, individuals exposed to the floods systematically tended to perceive a

Table 9
Emotional change in Japan (2014 and 2017).

Dependent variables	Participants in 2014 Desperate feeling	Hopeless life	Something bad
Minor or half-damaged house dummy	0.0634	0.0974	0.0138
	(0.0813)	(0.0459)	(0.0605)
Almost or Totally Collapsed House Dummy	0.288	0.194	0.0615
	(0.104)	(0.0756)	(0.0814)
Observations	186	185	183

Dependent variables	Participants in 2017 Desperate feeling	Hopeless life	Something bad
Minor or half damaged house dummy	0.0881	0.100	−0.00417
	(0.0784)	(0.0457)	(0.0593)
Almost or Totally Collapsed House Dummy	0.319	0.142	0.0301
	(0.0998)	(0.0674)	(0.0770)
Observations	179	179	176

Notes: Robust standard errors are reported in parentheses. Desperate Feeling takes 1 if individuals feel that their lives are desperate. Hopeless Life takes 1 if they feel that their lives are hopeless. Something Bad takes 1 if they feel that something bad will happen in the future. Minor or Half-damaged House is the group indicating that subjects whose houses suffered minor or half damage. Almost or Totally-collapsed House is the group indicating subjects whose houses had almost or totally collapsed.

Table 10
Emotional change in Japan (2014 and 2017): Bound approach.

Dependent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Experiments in 2014						Experiments in 2017					
	Desperate feeling		Hopeless life		Something bad		Desperate feeling		Hopeless life		Something bad	
Minor or half-damaged house dummy	0.0864		0.135		0.0323		0.179		0.110		−0.0115	
	(0.135)		(0.0624)		(0.0665)		(0.0997)		(0.0524)		(0.0511)	
Almost or totally-collapsed house dummy		0.291		0.227		0.0655		0.384		0.162		0.0231
		(0.135)		(0.0849)		(0.0741)		(0.0861)		(0.0568)		(0.0589)
Observations	186	186	185	185	183	183	179	179	179	179	176	176

Notes: We follow Oster (2019) to calculate bounding values for unbiased coefficients. Bootstrap standard errors in parentheses. We control for sex, age and smoking dummy and set the maximal R^2 to 1.3 times the R^2 of each regression. Minor or Half-damaged House is the group indicating that subjects whose houses suffered minor or half damage. Almost or Totally-collapsed House is the group indicating subjects whose houses had almost or totally collapsed.

decrease in their life expectancy. Overall, our results for both Japan and the Philippines seem to be consistent with the frameworks proposed by Callen et al. (2014), Callen (2015).[30]

7.3. Alternative explanation: Liquidity constraints

However, as Callen (2015) points out, a change in consumption levels due to economics losses may also affect individuals' patience: scarcity of monetary resources or simply binding liquidity constraints may make people "seemingly" present biased.[31] Here, we examine this possible intervening channel, liquidity constraints.

In the case of Japan, no respondent in the JAGES survey claimed money shortage for food purchases, indicating that liquidity constraints were not binding among the subjects. In fact, the general probability of binding liquidity constraint is negligible in Japan even during the financial crisis in 1997–98 (Sawada et al., 2011). However, in the Philippines, our data show that 54% of the subjects could not borrow money from others during their need after the disaster. Hence, we re-estimate the impact of the disaster on preference parameters only for the Philippines.

A long-standing critique of the CTB is that non-liquidity constrained individuals should not reveal any of their intertemporal preferences in money allocation tasks (Augenblick et al., 2015; Andreoni et al., 2018). Arbitrage over money rewards may be stripping present bias from the data and invalidating cash for measuring discounting. In other words, deriving the estimation model from a utility maximization is only theoretically appropriate when a subject is constrained (or bracketing narrowly).

[30] There are alternative mental health and emotional channels following the psychology literature such as Loewenstein et al. (2001) and Haushofer and Fehr (2014). It would be possible that disaster-hit subjects perceive that they are in a loss domain, making them more open to taking risks. Alternatively, individuals under extreme stress are simply less likely to analyze the set of gambling choices carefully and use instead a simple rule such as choosing the gamble that can give the highest payoff (Janis, 1993), leading to a systematic observation that disaster exposure makes lower risk-aversion.

[31] Losing financial resources, physical assets, and family members can consume attentional resources, leading to distinctive biases on cognitive function and particular decisions. Mani et al. (2013) shows that scarcity can impede one's cognitive functions, leading to seemingly myopic behaviors. Carvalho et al. (2016) also argues that scarce resources can affect one's willingness to delay gratification, and those who suffered from liquidity constraints behaved as if they were more present-biased.

Table 11
Emotional change in Japan (2014 and 2017): Weighted approach.

(A) Weight variable: Stayer

Experiments in 2014	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variables	Desperate feeling	Hopeless life	Something bad	Desperate feeling	Hopeless life	Something bad	Desperate feeling	Hopeless life	Something bad	Desperate feeling	Hopeless life	Something bad
Minor or half-damaged house dummy	0.0743	0.0906	0.00923	0.0604	0.0976	0.0140	0.0331	0.106	0.0214	0.0642	0.0989	0.0154
	(0.0921)	(0.0454)	(0.0588)	(0.0818)	(0.0459)	(0.0604)	(0.0893)	(0.0463)	(0.0572)	(0.0810)	(0.0460)	(0.0603)
Almost or totally-collapsed house dummy	0.285	0.170	0.0936	0.286	0.192	0.0616	0.275	0.178	0.0813	0.289	0.197	0.0633
	(0.113)	(0.0727)	(0.0901)	(0.104)	(0.0752)	(0.0813)	(0.112)	(0.0735)	(0.0841)	(0.103)	(0.0760)	(0.0814)
Observations	186	185	183	186	185	183	186	185	183	186	185	183
P-value of the null hypothesis for homogeneous parameters	0.0355	0.0245	0.556	0.0183	0.0133	0.742	0.0265	0.0112	0.627	0.0168	0.0115	0.733
Weight variable	Age	Age	Age	Sex	Sex	Sex	Education	Education	Education	Smoking	Smoking	Smoking

Experiments in 2017	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variables	Desperate feeling	Hopeless life	Something bad	Desperate feeling	Hopeless life	Something bad	Desperate feeling	Hopeless life	Something bad	Desperate feeling	Hopeless life	Something bad
Minor or half-damaged house dummy	0.0344	0.0773	−0.0225	0.0765	0.105	−0.0102	0.115	0.105	0.00828	0.0896	0.104	−0.000864
	(0.0856)	(0.0424)	(0.0590)	(0.0802)	(0.0439)	(0.0603)	(0.0870)	(0.0451)	(0.0669)	(0.0780)	(0.0461)	(0.0592)
Almost or totally-collapsed house dummy	0.300	0.0989	0.0361	0.318	0.147	0.0299	0.390	0.175	0.0292	0.322	0.146	0.0360
	(0.108)	(0.0561)	(0.0843)	(0.101)	(0.0665)	(0.0791)	(0.102)	(0.0788)	(0.0841)	(0.0996)	(0.0683)	(0.0779)
Observations	178	178	175	179	179	176	179	179	176	179	179	176
P-value of the null hypothesis for homogeneous parameters	0.0137	0.0818	0.737	0.0070	0.0124	0.858	0.0008	0.0122	0.941	0.0058	0.0208	0.869
Weight Variable	Age	Age	Age	Sex	Sex	Sex	Education	Education	Education	Smoking	Smoking	Smoking

(B) Weight variable: Total

Experiments in 2014	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variables	Desperate feeling	Hopeless life	Something bad	Desperate feeling	Hopeless life	Something bad	Desperate feeling	Hopeless life	Something bad	Desperate feeling	Hopeless life	Something bad
Minor or half-damaged house dummy	0.0712	0.0996	0.00477	0.0608	0.0976	0.0140	0.0758	0.0939	0.0106	0.0635	0.0976	0.0139
	(0.103)	(0.0471)	(0.0593)	(0.0817)	(0.0459)	(0.0604)	(0.0804)	(0.0466)	(0.0623)	(0.0813)	(0.0459)	(0.0604)
Almost or totally-collapsed house dummy	0.249	0.161	0.0855	0.286	0.192	0.0616	0.291	0.202	0.0529	0.288	0.195	0.0617
	(0.121)	(0.0711)	(0.0893)	(0.104)	(0.0752)	(0.0813)	(0.104)	(0.0784)	(0.0827)	(0.104)	(0.0756)	(0.0814)
Observations	186	185	183	186	185	183	186	185	183	186	185	183
P-value of the null hypothesis for homogeneous parameters	0.104	0.0199	0.590	0.0182	0.0132	0.742	0.0189	0.0152	0.803	0.0175	0.0127	0.741
Weight variable	Age	Age	Age	Sex	Sex	Sex	Education	Education	Education	Smoking	Smoking	Smoking

Experiments in 2017	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variables	Desperate feeling	Hopeless life	Something bad	Desperate feeling	Hopeless life	Something bad	Desperate feeling	Hopeless life	Something bad	Desperate feeling	Hopeless life	Something bad
Minor or half-damaged house dummy	0.0294	0.0802	−0.0149	0.0769	0.105	−0.0101	0.0821	0.0991	−0.00692	0.0892	0.103	−0.00179
	(0.0878)	(0.0462)	(0.0613)	(0.0801)	(0.0440)	(0.0603)	(0.0782)	(0.0464)	(0.0591)	(0.0781)	(0.0460)	(0.0592)
Almost or totally-collapsed house dummy	0.281	0.0901	0.0268	0.318	0.147	0.0299	0.301	0.134	0.0303	0.321	0.145	0.0343
	(0.110)	(0.0565)	(0.0824)	(0.101)	(0.0666)	(0.0791)	(0.101)	(0.0665)	(0.0773)	(0.0996)	(0.0680)	(0.0776)
Observations	178	178	175	179	179	176	179	179	176	179	179	176
P-value of the null hypothesis for homogeneous parameters	0.0231	0.123	0.857	0.0069	0.0126	0.858	0.0119	0.0334	0.871	0.0060	0.0219	0.874
Weight variable	Age	Age	Age	Sex	Sex	Sex	Education	Education	Education	Smoking	Smoking	Smoking

Notes: Robust standard errors in parentheses. Minor or Half-damaged House is the group indicating that subjects whose houses suffered minor or half damage. Almost or Totally-collapsed House is the group indicating subjects whose houses had almost or totally collapsed. Age refers to the age of the participants. Sex is equal to 1 for male participants. Education takes 1 for participants with complete compulsory education and 0 otherwise. Smoking" takes 1 when they smoke sometimes or almost every day and 0 otherwise.

Table 12
Emotional change in the Philippines (2018).

Dependent variable	𝟙[Subjective life expectancy declined]	
	(1)	(2)
Flood damage dummy	0.103	0.120
	(0.0604)	(0.0622)
Observations	87	87
Control variables	No	Yes

Notes: Robust standard errors are reported in parentheses. 𝟙(Subjective Life Expectancy Declined) takes 1 if subjects perceive a decline in their longevity after Habagat. Flood Damage is the group indicating subjects whose households experienced at least three kinds of damages, including farm damage, as identified by the satellite image. Control variables include sex, age, years of education, and expected life expectancy.

Table 13
Individual utility parameters estimated by the Convex Time Budget (CTB) experiments allowing for heterogeneity by damages and liquidity constraints in the Philippines (2014 and 2018).

Dependent variables	(1)	(2)	(3)	(4)	(5)	(6)
	Experiments in 2014			Experiments in 2018		
	β	δ	α	β	δ	α
Flood damage dummy	−0.195	0.00804	−0.0903	−0.325	−0.0132	−0.374
	(0.0917)	(0.0159)	(0.327)	(0.106)	(0.0199)	(0.433)
Liquidity constraint dummy	−0.129	0.0176	0.291	−0.0381	0.0300	0.937
	(0.0913)	(0.0113)	(0.263)	(0.107)	(0.0143)	(0.371)
ln(Income)	0.0177	0.00265	0.0585	0.0121	0.00251	0.00784
	(0.00818)	(0.00211)	(0.0439)	(0.0118)	(0.00237)	(0.0614)
Observations	98	98	98	91	91	91

Notes: Robust standard errors are reported in parentheses. Flood Damage is the group indicating subjects whose households experienced at least three kinds of damages, including farm damage, as identified by the satellite image. Liquidity Constraint dummy takes 1 if the participant could not borrow money from others during their need after Habagat. Income is the household income before Habagat.

To assuage these concerns, we employ the following approach. First, we follow Andreoni and Sprenger (2012) and model consumption external to the experiment study in the proceeding method.

$$ln(\frac{x_t+\omega_1}{x_{t+k}+\omega_2}) = -\frac{ln(\beta)}{\alpha}\mathbb{1}[t=0] - \frac{ln(\delta)}{\alpha}k - \frac{1}{\alpha}ln(P), \tag{11}$$

where the terms ω_1 and ω_2 are additional utility parameters which could be interpreted as background consumption. In our specification, these parameters are set to 60PHP, the average value of daily consumption in the East Laguna Village in 2012. With this model, we estimate β, δ and α at the individual level.

Second, we estimate the following empirical model of the disaster impact, regressing each of the estimated preference parameters on the damage variable as well as the liquidity constraint and income variables:

$$y_i = b_0 + b_1 Flood\,Damage_i + b_2\mathbb{1}[LiquidityConstraint_i] + b_3 ln(Income_i) + \varepsilon_i, \tag{12}$$

where y_i is the estimated preference parameter (β, δ or α), $\mathbb{1}[LiquidityConstraint_i]$ is an indicator function, which takes 1 when a subject cannot borrow money from others during their need after the disaster and 0 otherwise, and $ln(Income_i)$ is the subject's income. If the subject cannot borrow money from others during their need after the disaster, liquidity constraint is more likely to be binding. Moreover, if the subject earns more income, the subject has enough money for consumption smoothing and liquidity constraint is less likely to bind. Thus, these two variables, $\mathbb{1}[LiquidityConstraint_i]$ and $ln(Income_i)$, are proxies for liquidity constraints. If damages may make people "seemingly" present biased by reinforced liquidity constraints due to economic losses, b_1 is statistically insignificant due to these two controls.

The results reported in Table 13 for 2014 and 2018, respectively show that even with liquidity constraint controls the estimated β is still systematically lower at the 10% significance level for those exposed to the floods than those unexposed. This finding suggests that the inclusion of the liquidity constraint cannot fully explain the reinforced present bias caused by a disaster. Our overall results seem to favor the psychological channel over the liquidity constraint channel.

Yet, we also find that the effect on β becomes smaller uniformly once we incorporate the liquidity constraint variables into the estimation model. This could be seen consistent with Carvalho et al. (2016) which finds seeming present bias among those who face liquidity constraints if allowing heterogeneous behavioral response to binding liquidity constraints in the model. Hence, we cannot rule out the possibility that the combination of psychological factors and liquidity constraints could be driving our result.

8. Concluding remarks

To investigate whether and how long preferences are affected by extreme events, we adopt the CTB and MPL experiments and employed accurate damage information from official metrical surveys and satellite images. We find that disaster exposure seems to make individuals more present-biased over the short and long time intervals between two distinct sets of subjects in Japan and the Philippines with different socioeconomic conditions and disaster types. As for the potential channels, our results are largely consistent with Callen et al. (2014), Callen (2015), suggesting that the psychological responses and changes in survival expectations contribute to individuals' impatience.

The literature on hyperbolic discounting attributes harmful behaviors, such as obesity, overeating, debt overhang, gambling, smoking, drinking, and other procrastination behaviors, to naive hyperbolic discounting (Banerjee and Mullainathan, 2010). Our companion study reveals that present bias reinforced by disasters seems to induce unhealthy behaviors such as overeating, smoking, and drinking among the same subjects as this study (Sawada et al., 2019), as well as depression among tsunami and nuclear power plant disaster victims in Japan (Sawada et al., 2023). Hence, we believe that our study also sheds new light on post-disaster rehabilitation policies by emphasizing the importance of providing commitment devices to disaster victims for mitigating negative behavioral consequences of reinforced present bias, in line with Dupas (2011), Giné et al. (2010), and Bryan et al. (2010).

Yet, we should also note that there are potential caveats of our study. The recent experimental literature on hyperbolic discounting focuses on the difference between the domains of monetary and non-monetary choice. Considering the empirical result by Augenblick et al. (2015), which finds that present bias in monetary choices is much more limited than that in the allocation of work, our results that are fully based on monetary choices may underestimate the true impacts of disasters on real-world behavior. Using the timings of mailing New Year's cards to identify present bias and hyperbolic discounting after the disaster in the non-monetary domain following Sawada et al. (2023)[32], we find 45% of our subjects in Iwanuma show hyperbolic discounting, while the CTB experiment shows that 36% of quasi-hyperbolic discount parameter, β, of Iwanuma's subjects fall below one. This indicates that present bias in non-monetary choices is more salient than that in monetary choices. While a recent article by Balakrishnan et al. (2020) also shows that present bias even for money exists for immediate payments using the Kenyan mobile money system M-Pesa, we would need to be aware of potential bias in estimating hyperbolic discounting parameter with different monetary incentives.

Also, there are issues which need further investigations. First, as Frederick et al. (2002) pointed, the variability in the estimates might have been driven by other confounding factors which were not considered in this study. Such factors may include intertemporal arbitrage in general, uncertainty, expectations of changing utility functions, and habit formation. Second, we find that disaster exposure in Japan reinforces risk tolerance in the MPL experiment, but induces no change in the intertemporal elasticity of substitution in the CTB experiment. Since under the expected utility hypothesis, the coefficient of relative risk aversion is the reciprocal of the intertemporal elasticity of substitution, our empirical results may be seen consistent with the framework of Kreps and Porteus (1978) and Epstein and Zin (1991), rejecting the expected utility hypothesis. Third, since social preferences are also susceptible to instability over time, as the pandemic has revealed, pro-sociality needs to be examined. Our companion papers, Kuroishi and Sawada (2019) and Sawada et al. (2023), analyzed altruism using dictator games and real-world decisions, respectively. We believe these issues are beyond the scope of the current paper and leave them as future investigations.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.euroecorev.2023.104632.

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[32] Sawada et al. (2023) uses 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, meaning that Japanese people sent around 30 New Year's cards each. Since New Year's cards are ideally supposed to 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. Yet, it is not uncommon for people to delay sending cards because cards received by January 7 are still socially acceptable, albeit not necessarily desirable. Hyperbolic discounters would procrastinate writing and sending cards due to time devoted to the costly activity of writing new year cards.

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