# Chapter 2

# How Does a Natural Disaster Affect People's Preference? The Case of a Large Scale Flood in the Philippines Using the Convex Time Budget Experiments

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# CHAPTER 2

# How Does a Natural Disaster Affect People's Preference? The Case of a Large Scale Flood in the Philippines Using the Convex Time Budget Experiments

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*This paper is an attempt to contribute to the literature on individual preferences and disasters by investigating the impact of a natural disaster on present bias, time discount, and risk aversion parameters, which are elicited by using a new experimental technique called the Convex Time Budget (CTB) experiments, developed by Andreoni and Sprenger (2012), as well as a more common method called the Double Multiple Price List (DMPL) experiments of Andersen, Harrison, Lau and Rutström (2009). We also conducted canonical dictator games to elicit degree of altruism, one of the most widely analysed social preferences. Based on these methods, we employed a unique experimental data set collected from a village in the Philippines, which was hit by a strong flood in 2012. Our focus is on the overall impact of the flood on preferences and decisions. We found the following three empirical results: First, the CTB experiments offer reasonable levels of time discounting, curvature and quasi-hyperbolic discounting in the whole sample. Second, this quasi-hyperbolic discounting in a Filipino village is contrasted with the dynamically consistent time preferences in the United States found by Andreoni and Sprenger. Finally, we found that being hit by the flood made individuals significantly more present-biased than those who were unaffected by the flood.*

**Keywords:** Convex Time Budget experiment, Natural Disaster, Risk and Time Preference

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# 1. Introduction

Recently, a number of devastating natural disasters have hit both developed and developing countries. Hundreds of thousands of lives were lost in the 2013 Typhoon Haiyan (Yolanda) in the Philippines, the 3/11 compounded disaster in Tohoku, Japan in 2011, and the 2008 Sichuan earthquake in China. In 2011, the floods in Thailand involved relatively few human casualties, but caused USD 45.7 billion in damage, mainly to the manufacturing sector, as seven major industrial estates were inundated by floods. Disasters can have serious negative effects not only in terms of lives lost, but also on the livelihoods of survivors in the aftermath of the disaster.

In preparation for and response to the wide variety of shocks caused by natural disasters, people can adopt market insurance mechanisms, make use of government ex ante and ex post support, and use informal mutual insurance mechanisms in their community. To improve complementarities among these market, state, and community insurance mechanisms, we need to understand the roles of individual decisions and behaviours. In particular, we need to examine how individual and social preferences—the foundations of decision-making—are affected by disasters.

In economics, individual preference parameters have long been treated as “deep parameters,” i.e., as given and thus constant over time (e.g., Stigler and Becker, 1977). Moreover, the pro-social behaviours or social preferences of individuals, usually modeled as a deviation from Nash equilibrium, have been regarded as "irrational" decisions. Studies on endogenous formation of individual and social preferences have only recently started to emerge, finding that they are not constant over time and that they change under some circumstances (Fehr and Hoff, 2011). As natural disasters and manmade disasters are traumatic events, they are likely to affect an individual’s behaviour in the short term and possibly in the long term. Notable examples of such studies, on the Indian Ocean tsunami in 2004, are Cameron and Shah (2011) and Cassar, *et al.* (2011), as well as Callen, *et al*. (2014) on Afganistan, and Voors, *et al*. (2012) on Burundi. Cameron and Shah (2012) found that, in Indonesia, individuals who suffered a flood or earthquake in the past three years are more risk averse than those who did not. Cassar, *et al.* (2011)

showed that after the tsunami in Thailand, individuals who were affected by the disaster were substantially more trusting, risk averse and trustworthy. They found that individual-level welfare and aggregate growth-level are affected by changes in these social preferences. Callen, *et al*. (2014) investigated the relationship between violence and economic risk preferences in Afghanistan, finding a strong preference for certainty and violation of the expected utility framework. Most importantly, Voors, *et al*. (2012) used a series of field experiments in rural Burundi to find that individuals exposed to violence display more altruistic behaviour towards their neighbors and are more risk seeking. The results indicate that large shocks can have long-term consequences for non-market insurance mechanisms. While there have been developed empirical studies on household behaviour toward risks in developing countries, changes in individual parameters and behaviours by disasters still have remained to be largely identified.

In this paper we investigate the impact of a natural disaster on present bias, time discount, and risk aversion parameters, which are elicited by a new experimental technique called the Convex Time Budget (CTB) experiments, developed by Andreoni and Sprenger (2012) as well as the canonical experiments called the Double Multiple Price List (DMPL) experiments of Andersen, *et al*. (2008), in an integrated manner. We employ a unique experimental data set collected from a village in the Philippines, which was hit by a strong flood in 2012. Our focus is on the overall impact of the flood on preferences and decisions. Indeed, the Philippines suffers from tropical depression and typhoons nearly every year the country experiences about 20 tropical storms on average every year, usually occurring during the monsoon season from June to December.

## 2. Data

We studied residents in East Laguna village, which is located in the Pila municipality of Laguna province, approximately 80 kilometers south of Metro Manila, facing the east coast of Laguna de Bay. Its proximity to the International Rice Research Institute (IRRI), which is located in Los Baños and 20 kilometers away from the village, has enabled researchers to conduct surveys in cooperation with IRRI. The earliest documented survey carried out in the village dates back to 1966, when a Japanese geographer, Hiromitsu Umehara (1967), conducted and reported the results of a total enumeration survey. After Umehara's first survey, 18 rounds of household surveys were conducted from 1974 to 2007 in collaboration with IRRI (Sawada, *et al*., 2012). Surveys in the 1970s, 1980s, and 1990s were organised predominantly by Professor Yujiro Hayami and Professor Masao Kikuchi, who made numerous international academic contributions (Hayami and Kikuchi, 2000). They found that due to the increase in rice production and the fall in the price of rice, both of which were to some extent induced by the Green Revolution and land reform implementation, the income of agricultural households and food consumption of poor households increased significantly. They also found that a boost in non-agricultural income was a result of investment in education financed by the increased income from agricultural activities. In the 2000s, five further rounds of surveys were conducted by other researchers (Fuwa, *et al*., 2006; Kajisa, 2007; Sawada, *et al*., 2012). Due to these numerous surveys, a lot of benchmark information on the village has been collected, compiled, and carefully analysed.

In August 2012, the village was hit by serious flooding due to the southwest monsoon rains, also known as "habagat" in Tagalog. It had started with an eight-day period of torrential rains and thunderstorms in the Philippines from August 1st to August 8th. Its effects centered on Metro Manila, the surrounding provinces of the CALABARZON Region (Quezon, Cavite, Laguna and Rizal provinces) and the provinces of Region 3 (Bulacan, Pampanga and Bataan Provinces). Not a typhoon in its own right, the storm was a strong movement of the southwest monsoon "habagat" caused by the pull of Typhoon Saola (Gener) from August 1-3, strengthened by Typhoon Haikui. It caused typhoon-like damage such as river overflow and landslides to the region. In Laguna province, where East Laguna Village is located, "habagat" spawned flooding that submerged low-lying villages in 19 towns and cities including the village, destroying PhP 410.3 million worth of agriculture products. The damaged crops were planted in about 11,000 hectares of inundated farmlands of rice, corn and crops, and affected some 6,000 farmers. More than a half of the village area was submerged by floodwater, causing great damage to rice paddies.

We employ survey and experimental data collected exclusively for this study. The subjects were selected from the farmers in East Laguna village and surrounding villages. A total of 161 farmers participated in our field experiments on March 20th (34 participants), March 21st (32 participants), March 22nd (38 participants), March 23rd (40 participants), and March 24th (17 participants) in 2014.

## 3. Estimation Models

We carefully design and conduct two types of experiments to elicit present bias, time discount, and risk aversion parameters: First, we adopt a new experimental technique called the Convex Time Budget (CTB) experiments developed by Andreoni and Sprenger (2012); and second, we employ the canonical experiments called the Double Multiple Price List (DMPL) experiments of Andersen, *et al*. (2008). The data collected by both the CTB and DMPL experiments in the village are used to separately identify the three key parameters of the utility function: risk aversion parameter, 1-α; time discounting parameter, δ; and present bias parameter, β.

For the CTB and the DMPL, we assume a quasi-hyperbolic discounting structure for discounting and the preferences described by:

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

where the parameter δ captures standard long-run exponential discounting, and the parameter β captures a specific preference towards payments in the present, $t = 0$. While present bias is associated with $\beta < 1$, $\beta = 1$ corresponds to the case of standard exponential discounting. Also, $1-\alpha$ represents the coefficient of relative risk aversion.

### 3.1.The Convex Time Budget (CTB) Experiment

In the CTB experiment of Andreoni, *et al.* (2013), subjects are given the choice of ($X$, 0), (0, $Y$) or anywhere along the intertemporal budget constraint connecting these points, such that $Px_t + x_{t+k} = Y$, where $P = \frac{Y}{X}$ is the gross interest rate. In this setting, we can maintain a standard intertemporal Euler equation:

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

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

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

Assuming an additive error structure, this is estimable at either the whole group or individual level.

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

$$x_t = \frac{400(\beta^{t_0}\delta^k P)^{\frac{1}{\alpha-1}}}{1+P(\beta^{t_0}\delta^k P)^{\frac{1}{\alpha-1}}} \tag{4}$$

which avoids the problem of the logarithmic transformation in (2).

### 3.2.The Double Multiple Price List (DMPL) Experiment

The DMPL consists of two stages (Andersen, *et al.*, 2008). The first stage is designed to identify discounting. The second stage is designed to unconfound the first stage by providing information on utility function curvature through risky choice.

#### *3.2.1. The Multiple Price List (MPL) Experiment*

In the Multiple Price List (MPL) experiment, individuals make a series of binary choices between smaller sooner payments $X$ and larger later payments

$Y$. The point in each price list where an individual switches from preferring the smaller sooner payment to the larger later payment carries interval information on discounting. In MPL, we assume α = 1. Then, from Andersen, *et al*. (2008), the probability of choosing the smaller sooner payments $X$ can be formalised as:

$$Pr(Choice = X) = \frac{(\beta^{t_0}\delta^k X)^{\frac{1}{\nu}}}{(\beta^{t_0}\delta^k X)^{\frac{1}{\nu}} + (\beta^{t_0}\delta^k Y)^{\frac{1}{\nu}}} \tag{5}$$

where ν represents stochastic decision error. On the other hand, the probability of choosing the larger later payment is

$$Pr(Choice = Y) = \frac{(\beta^{t_0}\delta^k Y)^{\frac{1}{\nu}}}{(\beta^{t_0}\delta^k X)^{\frac{1}{\nu}} + (\beta^{t_0}\delta^k Y)^{\frac{1}{\nu}}} \tag{6}$$

In order to estimate parameters, β, δ, and ν, we can maximise the following conditional log-likelihood function:

$$lnL(\beta, \delta, \nu; X, Y) = \sum_i \mathbf{1}\{Choice = X\} ln(Pr(Choice = X) + \mathbf{1}\{Choice = Y\} ln(Pr(Choice = Y) \tag{7}$$

*3.2.2 The Holt and Laury (2002) Experiment*

The Holt and Laury (2002) experiment is one of the most popular experiments to elicit an individual's attitude toward risks. In the Holt and Laury (2002) experiment, subjects face a series of decisions between a safe and risky binary (gamble) choice. The probability of the high outcome in each gamble increases as one proceeds through the task,such that where a subject switches from the safe to the risky gamble carries information on risk attitudes. In Holt and Laury, there are two options, A and B. For each outcome of each option A and B, the probability $p(M_{ij})$ is assigned by the experimenter. Then, the expected utility for lottery i (i

= A or B) is

$$EU_i = \sum_{j=1,2} (p(M_{ij}) \times M_{ij}^{\alpha}) \qquad (8)$$

The probability of choosing the safe binary gamble, the option A, is

$$Pr(Choice = A) = \frac{EU_A^{\frac{1}{\mu}}}{EU_A^{\frac{1}{\mu}} + EU_B^{\frac{1}{\mu}}} \qquad (9)$$

where μ represents stochastic decision error. On the other hand, the probability of choosing the risky binary gamble, option B, is

$$Pr(Choice = B) = \frac{EU_B^{\frac{1}{\mu}}}{EU_A^{\frac{1}{\mu}} + EU_B^{\frac{1}{\mu}}} \qquad (10)$$

Then the conditional log-likelihood function to estimate parameters, α and μ, is

$$lnL(\alpha, \mu; A, B) = \sum_i \mathbf{1}\{Choice = A\} ln(Pr(Choice = A) + \mathbf{1}\{Choice = B\} ln(Pr(Choice = B) \qquad (11)$$

*3.2.3. The Double Multiple Price List (DMPL) Experiment*

Combining the two multiple price list experiments shown above, in the double multiple price list (DMPL) experiments, the joint likelihood of the curvature and discount rate becomes:

$$lnL(\beta, \delta, \alpha, \mu, \nu; X, Y, A, B) = lnL^{RA} + lnL^{DR} \qquad (12)$$

which is maximised using standard numerical methods.

# 4. Results

## 4.1. The Convex Time Budget (CTB) Experiment

Table 2.1 shows the estimation results of the curvature parameter, α, which is associated with risk aversion parameter, 1- α; time discounting parameter, δ; and present bias parameter, β. The first two columns report the estimated parameter based on equation (4) using non-linear least squares (NLS) and the last column shows results based on equation (3) using ordinary least squares (OLS). In all specifications, the estimated present bias parameter falls significantly below one, indicating substantial quasi-hyperbolic discounting in the whole sample. Time discount and risk aversion parameters are within a reasonable range.

**Table 2.1: The Results of Aggregate CTB**

| | (1) NLS | (2) NLS | (3) OLS |
|---|---|---|---|
| $\beta$ | 0.827*** | 0.827*** | 0.788*** |
| | (0.0166) | (0.0204) | (0.0266) |
| $\delta$ | 0.993*** | 0.993*** | 0.992*** |
| | (0.000272) | (0.000639) | (0.000868) |
| $\alpha$ | 0.738*** | 0.738*** | 0.854*** |
| | (0.0130) | (0.0200) | (0.0134) |
| Clustered SE's | No | Yes | Yes |
| $N$ | 2880 | 2880 | 2880 |

Standard errors in parentheses

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

In order to examine the impact of disasters, we re-estimate the model allowing for a heterogenous risk aversion associated parameter, α; time discounting parameter, δ; and present bias parameter, β, depending on the seven damage types: (1) overall damage; (2) house damage; (3) farm damage; (4) asset damage; (5) income loss; (6) increasing in debt; and (7) sickness or injury. The results are shown in Table 2.2 where subscript "zero" and "one" indicate "without damage" and "with damage," respectively. In this table, we can verify that the disaster affected the present bias parameter negatively though not necessarily significantly. Only house damage caused negative and significant impact on the present bias parameter.

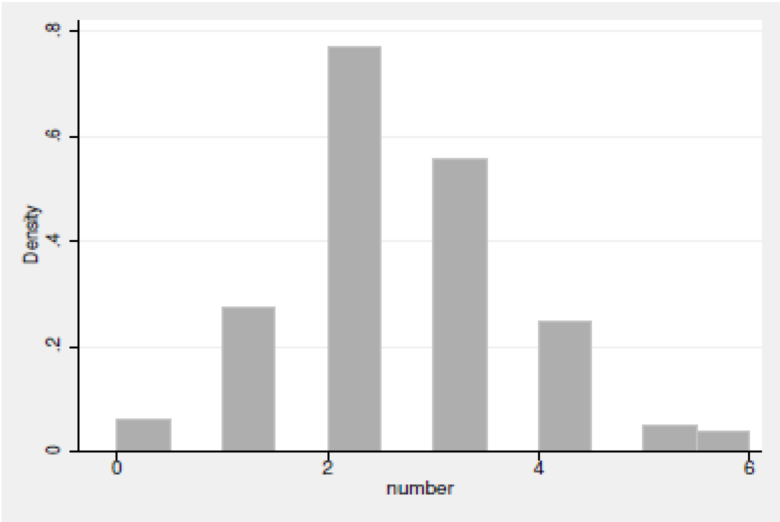
**Table 2.2.: The Effect of Habagat on Deep Parameters in CTB**

| | (1) None | (2) House | (3) Farm | (4) Assets | (5) Income | (6) Debt | (7) Sick or Injured | (8) Day = 3 or 4 |
|---|---|---|---|---|---|---|---|---|
| $\beta_0$ | 0.878*** | 0.814*** | 0.773*** | 0.792*** | 0.837*** | 0.802*** | 0.796*** | 0.824*** |
| | (0.0783) | (0.0286) | (0.0647) | (0.0283) | (0.0520) | (0.0308) | (0.0284) | (0.0366) |
| $\beta_1$ | 0.784*** | 0.698*** | 0.791*** | 0.745*** | 0.775*** | 0.771*** | 0.721*** | 0.749*** |
| | (0.0275) | (0.0633) | (0.0290) | (0.0703) | (0.0307) | (0.0455) | (0.0756) | (0.0377) |
| $\delta_0$ | 0.993*** | 0.992*** | 0.992*** | 0.992*** | 0.991*** | 0.993*** | 0.992*** | 0.991*** |
| | (0.00269) | (0.000857) | (0.00182) | (0.000907) | (0.00246) | (0.000963) | (0.000874) | (0.00117) |
| $\delta_1$ | 0.992*** | 0.989*** | 0.991*** | 0.990*** | 0.992*** | 0.990*** | 0.990*** | 0.992*** |
| | (0.000901) | (0.00264) | (0.000988) | (0.00286) | (0.000893) | (0.00153) | (0.00371) | (0.00130) |
| $\alpha_0$ | 0.883*** | 0.862*** | 0.849*** | 0.854*** | 0.818*** | 0.865*** | 0.854*** | 0.852*** |
| | (0.0345) | (0.0143) | (0.0279) | (0.0141) | (0.0371) | (0.0166) | (0.0141) | (0.0196) |
| $\alpha_0$ | 0.852*** | 0.825*** | 0.855*** | 0.854*** | 0.863*** | 0.839*** | 0.850*** | 0.855*** |
| | (0.0140) | (0.0346) | (0.0152) | (0.0444) | (0.0139) | (0.0218) | (0.0433) | (0.0181) |
| $\beta_0 = \beta_1$ | 0.25 | 0.09 | 0.79 | 0.54 | 0.30 | 0.58 | 0.35 | 0.15 |
| $\delta_0 = \delta_1$ | 0.65 | 0.20 | 0.74 | 0.46 | 0.60 | 0.13 | 0.56 | 0.75 |
| $\alpha_0 = \alpha_1$ | 0.41 | 0.32 | 0.84 | 0.98 | 0.25 | 0.34 | 0.93 | 0.91 |
| Clustered SE's | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $N$ | 2880 | 2880 | 2880 | 2880 | 2880 | 2880 | 2880 | 2880 |

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

Figure 2.1 and Table 2.3 show the distribution of the incidence of damage caused by the flood. By using this damage information, we can construct a damage variable, which takes one if the incidence of damage is three or more; and takes zero if the incidence of damage is either one or two. We then allow the three deep parameters to differ depending on the damage status. The results are presented in Table 2.4 where subscript "zero" indicates "without damage" and "one" indicates "with damage." These estimation results indicate that individuals hit by the flood became significantly more present-biased than those unaffected by the flood.

## Figure 2.1: Damage Levels by Habagat




## Table 2.3: The Number of the Damages

| Item | Number | Per cent |
|---|---|---|
| 0 | 5 | 3 |
| 1 | 22 | 14 |
| 2 | 62 | 39 |
| 3 | 45 | 28 |
| 4 | 20 | 12 |
| 5 | 4 | 2 |
| 6 | 3 | 2 |
| Total | 161 | 100 |

*Source:Data_ExperimentGame_PilaMarch*2014

**Table 2.4: The Number of the Damages= 0/1 vs 4/5 or 0/1 vs 3/4/5/6**

| | (1) Severeness | (2) Severeness1 |
|---|---|---|
| $\beta_0$ | 0.861*** | 0.811*** |
| | (0.0495) | (0.0317) |
| $\beta_1$ | 0.640*** | 0.640*** |
| | (0.0802) | (0.0796) |
| $\delta_0$ | 0.992*** | 0.993*** |
| | (0.00190) | (0.000959) |
| $\delta_1$ | 0.989*** | 0.989*** |
| | (0.00320) | (0.00318) |
| $\alpha_0$ | 0.834*** | 0.864*** |
| | (0.0397) | (0.0158) |
| $\alpha_1$ | 0.822*** | 0.822*** |
| | (0.0455) | (0.0452) |
| $\beta_0 = \beta_1$ | 0.023 | 0.049 |
| $\delta_0 = \delta_1$ | 0.358 | 0.233 |
| $\alpha_0 = \alpha_1$ | 0.841 | 0.384 |
| $N$ | 1080 | 2112 |

Standard errors in parentheses

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

## 4.2 The Double Multiple Price List (DMPL) Experiment

Table 2.5 shows estimation results of the three parameters, together with error parameters, using the double multiple price list (DMPL) experiments. Again, we can verify substantial present- bias. Yet, risk aversion parameters are unreasonably high, which may be an artifact of the experimental data treatment: For the results shown in Table 2.5, we treat the multiple switchers in the Hold and Laury experiment as single switchers by considering the first switching point only. Naturally, this may cause upward bias of the estimated risk attitude parameter, making utility function convex rather than concave. To verify this reasoning, we split our sample into the individuals without multiple switching and with switching. As we can see from Table 2.7, the risk preference parameter is substantially smaller if we use the non-switching samples only. This result supports the upward bias of the estimated risk preference parameter we had already found.

**Table 2.5: The Results in Aggregate DMPL**

| | (1) DMPL | (2) HL | (3) MPL |
|---|---|---|---|
| $\beta$ | $0.516^{***}$ | | $0.608^{***}$ |
| | (0.062) | | (0.057) |
| $\delta$ | $0.970^{***}$ | | $0.974^{***}$ |
| | (0..0025) | | (0.002) |
| $\alpha$ | $1.254^{***}$ | $1.255^{***}$ | |
| | (0.158) | (0.082) | |
| $v$ | $0.383^{***}$ | | $0.363^{***}$ |
| | (0.062) | | (0.030) |
| $\mu$ | $0.554^{***}$ | $0.553^{***}$ | |
| | (0.060) | (0.049) | |
| Clustered SE's | Yes | Yes | Yes |
| $N$ | 17268 | 16692 | 3862 |

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

**Table 2.6: The Dummy Variable of Switching (Holt Laury)**

| Item | Number | Per cent |
|---|---|---|
| NO Switching | 85 | 53 |
| Switching | 76 | 47 |
| Total | 161 | 100 |

**Table 2.7: DMPL considering Switching**

| | (1) No Switching | (2) Switching |
|---|---|---|
| $\delta$ | $0.965^{***}$ | $0.975^{***}$ |
| | (0.00348) | (0.00349) |
| $v$ | $0.0906^{**}$ | $0.961^{***}$ |
| | (0.0314) | (0.183) |
| $\beta$ | $0.404^{***}$ | $0.697^{***}$ |
| | (0.0718) | (0.101) |
| $\alpha$ | $0.352^{**}$ | $2.451^{***}$ |
| | (0.123) | (0.183) |
| $\mu$ | $0.170^{**}$ | $0.459^{***}$ |
| | (0.0593) | (0.0340) |
| $N$ | 10500 | 6768 |

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

To examine the impact of disasters, we re-estimate the model allowing for a heterogenous risk aversion parameter, α; time discounting parameter, δ; and present bias parameter, β depending on the seven damage types: (1) overall damage; (2) house damage; (3) farm damage; (4) asset damage; (5) income loss; (6) increasing in debt; and (7) sickness or injury. The results are shown in Table 2.8, where subscript "zero" and "one" indicate "without damage" and "with damage,"respectively. The overall results in this table show that the disaster did not affect the present bias parameter negatively. The estimation results of the Holt and Laury (2002) experiments also show that the disaster did not affect risk preference parameter (Table 2.9).

**Table 2.8: The Effect of Habagat on Deep Parameters in DMPL**

| | (1) None | (2) House | (3) Farm | (4) Assets | (5) Income | (6) Debt | (7) Sick | (8) Day |
|---|---|---|---|---|---|---|---|---|
| $\delta_0$ | 0.970*** | 0.969*** | 0.965*** | 0.970*** | 0.972*** | 0.972*** | 0.969*** | 0.971*** |
| | (0.00682) | (0.00282) | (0.00540) | (0.00263) | (0.00448) | (0.00363) | (0.00262) | (0.00316) |
| $\delta_1$ | 0.969*** | 0.972*** | 0.970*** | 0.961*** | 0.968*** | 0.967*** | 0.975*** | 0.967*** |
| | (0.00259) | (0.00533) | (0.00282) | (0.00674) | (0.00302) | (0.00335) | (0.00774) | (0.00405) |
| $\nu_0$ | 0.549** | 0.353*** | 0.453*** | 0.372*** | 0.488*** | 0.322*** | 0.377*** | 0.444*** |
| | (0.186) | (0.0656) | (0.123) | (0.0649) | (0.122) | (0.0926) | (0.0628) | (0.0916) |
| $\nu_1$ | 0.374*** | 0.496** | 0.362*** | 0.472* | 0.344*** | 0.430*** | 0.440 | 0.302*** |
| | (0.0645) | (0.170) | (0.0711) | (0.221) | (0.0716) | (0.0848) | (0.317) | (0.0840) |
| $\beta_0$ | 0.766$^{+}$ | 0.531*** | 0.394*** | 0.518*** | 0.545*** | 0.491*** | 0.493*** | 0.535*** |
| | (0.437) | (0.0721) | (0.105) | (0.0658) | (0.124) | (0.0880) | (0.0643) | (0.0753) |
| $\beta_1$ | 0.508*** | 0.473*** | 0.547*** | 0.472*** | 0.504*** | 0.546*** | 0.720*** | 0.490*** |
| | (0.0618) | (0.117) | (0.0728) | (0.116) | (0.0710) | (0.0842) | (0.183) | (0.0999) |
| $\alpha_0$ | 2.304** | 1.237*** | 1.654*** | 1.229*** | 1.659*** | 1.000*** | 1.299*** | 1.506*** |
| | (0.825) | (0.181) | (0.392) | (0.168) | (0.355) | (0.240) | (0.166) | (0.217) |
| $\alpha_1$ | 1.214*** | 1.303*** | 1.157*** | 1.481*** | 1.116*** | 1.487*** | 0.861$^{+}$ | 0.955*** |
| | (0.160) | (0.319) | (0.171) | (0.443) | (0.172) | (0.212) | (0.471) | (0.225) |
| $\mu_0$ | 0.569*** | 0.546*** | 0.703*** | 0.559*** | 0.743*** | 0.508*** | 0.564*** | 0.605*** |
| | (0.146) | (0.0688) | (0.133) | (0.0657) | (0.127) | (0.104) | (0.0626) | (0.0750) |
| $\mu_1$ | 0.543*** | 0.574*** | 0.510*** | 0.481*** | 0.479*** | 0.565*** | 0.422* | 0.456*** |
| | (0.0623) | (0.125) | (0.0679) | (0.146) | (0.0692) | (0.0730) | (0.213) | (0.0960) |
| $\beta_0 = \beta_1$ | 0.558 | 0.672 | 0.230 | 0.729 | 0.774 | 0.651 | 0.241 | 0.722 |
| $\delta_0 = \delta_1$ | 0.963 | 0.609 | 0.356 | 0.192 | 0.435 | 0.250 | 0.456 | 0.444 |
| $\alpha_0 = \alpha_1$ | 0.194 | 0.857 | 0.244 | 0.595 | 0.250 | 0.128 | 0.379 | 0.077 |
| $N$ | 17268 | 17268 | 17268 | 17268 | 17268 | 17268 | 17268 | 17268 |

Clustered Standard errors in parentheses

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

**Table 2.9: The Effect of Habagat on Deep Parameters in Holt and Laury**

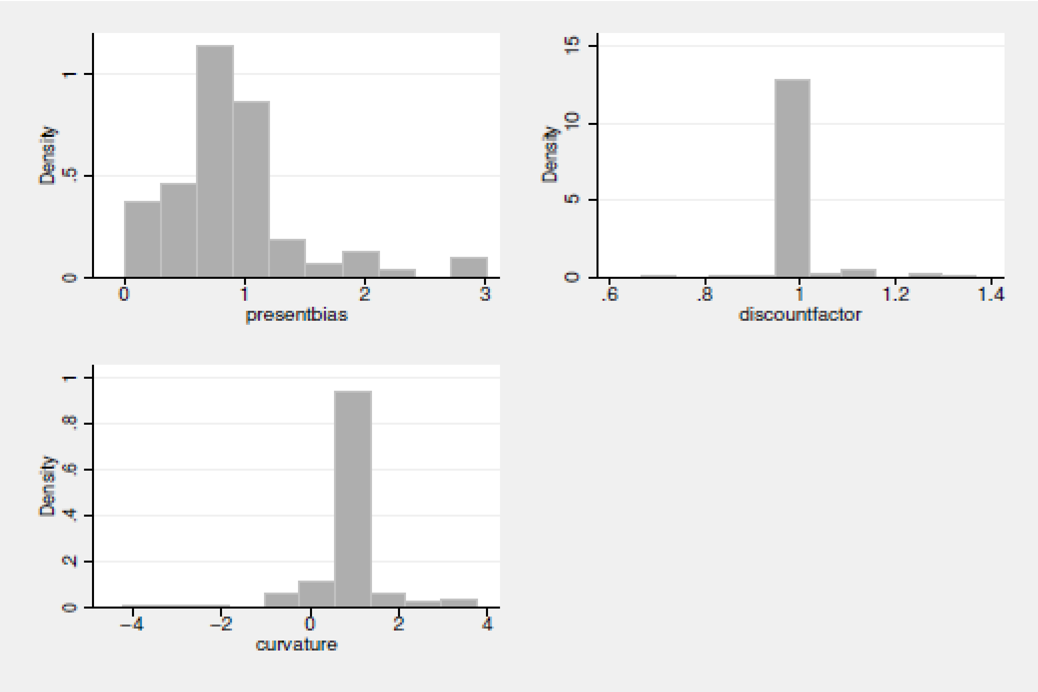
| | (1) None | (2) House | (3) Farm | (4) Assets | (5) Income | (6) Debt | (7) Sick |
|---|---|---|---|---|---|---|---|
| $\alpha_0$ | 2.304** | 1.238*** | 1.654*** | 1.230*** | 1.659*** | 1.000*** | 1.299*** |
| | (0.825) | (0.181) | (0.392) | (0.168) | (0.355) | (0.240) | (0.166) |
| $\mu_0$ | 0.569*** | 0.546*** | 0.703*** | 0.559*** | 0.743*** | 0.508*** | 0.564*** |
| | (0.146) | (0.0686) | (0.133) | (0.0655) | (0.127) | (0.104) | (0.0626) |
| $\alpha_1$ | 1.215*** | 1.303*** | 1.158*** | 1.481*** | 1.117*** | 1.488*** | 0.874+ |
| | (0.160) | (0.319) | (0.171) | (0.443) | (0.172) | (0.211) | (0.468) |
| $\mu_1$ | 0.543*** | 0.574*** | 0.510*** | 0.481*** | 0.479*** | 0.565*** | 0.426* |
| | (0.0622) | (0.125) | (0.0678) | (0.146) | (0.0690) | (0.0727) | (0.208) |
| $\mu_1$ | 0.543*** | 0.574*** | 0.510*** | 0.481*** | 0.479*** | 0.565*** | 0.426* |
| | (8.74) | (4.58) | (7.52) | (3.30) | (6.95) | (7.77) | (2.04) |
| $\alpha_0 = \alpha_1$ | 0.195 | 0.859 | 0.245 | 0.5977 | 0.168 | 0.127 | 0.391 |
| Clustered SE's | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $N$ | 720 | 720 | 720 | 720 | 720 | 720 | 720 |

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

## 4.3 The Convex Time Budget (CTB) Experiment: Individual Results

Based on the data from the convex time budget (CTB) experiments, we can also estimate the individual-level preference parameters. The distributions of each individual preference parameter are shown in Figure 2.2 and Table 2.10. While discount factor and risk parameters are clustered, we can see variations in the present bias parameter. We also examine the relationship between each parameter and observed characteristics captured by age and education level (Figure 2.3 and Table 2.11). While the correlation is not necessarily strong, we find negative correlation between present bias or time discount factor and education level. To validate this correlation, we run a quantile regression (Figure 2.4). These correlations can be found at a rather extreme level of parameters.

## Figure 2.2: The Distribution of Each Individual Deep Parameters




## Table 2.10: The Result of Individual CTB

| Statistics | Present Bias | Discount Factor | Curvature |
|---|---|---|---|
| Count | 120 | 120 | 120 |
| Mean | 2.32 | 1.04 | 1.14 |
| sd | 4.34 | 0.13 | 1.38 |
| p5 | 0.13 | 0.96 | -0.50 |
| p25 | 0.68 | 0.99 | 0.75 |
| Median | 0.88 | 0.99 | 0.91 |
| p75 | 1.09 | 1.00 | 0.94 |
| p95 | 15.20 | 1.39 | 4.36 |

**Figure 2.3: The Relationship between Deep Parameters, Age and Education**

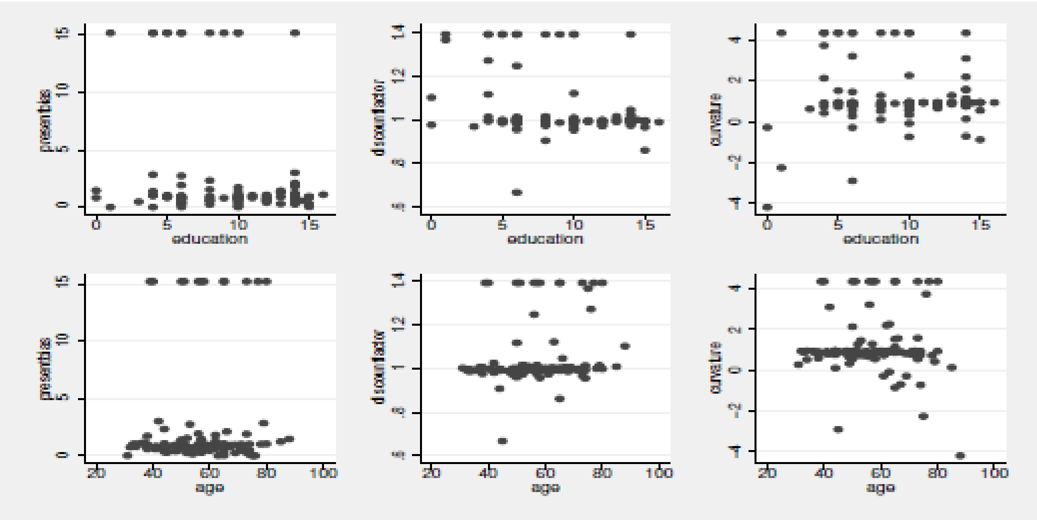



**Table 2.11: OLS Regression**

| | (1) presentbias | (2) discountfactor | (3) curvature |
|---|---|---|---|
| age | -0.000268 | 0.00108* | -0.0101 |
| | (0.00471) | (0.000515) | (0.00953) |
| education | 0.00538 | -0.00335 | 0.0462 |
| | (0.0144) | (0.00224) | (0.0329) |
| _cons | 0.856** | 0.973*** | 0.895+ |
| | (0.294) | (0.0340) | (0.453) |
| $N$ | 108 | 108 | 108 |

Standard errors in parentheses

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

**Figure 2.4: The Quantile Regression**

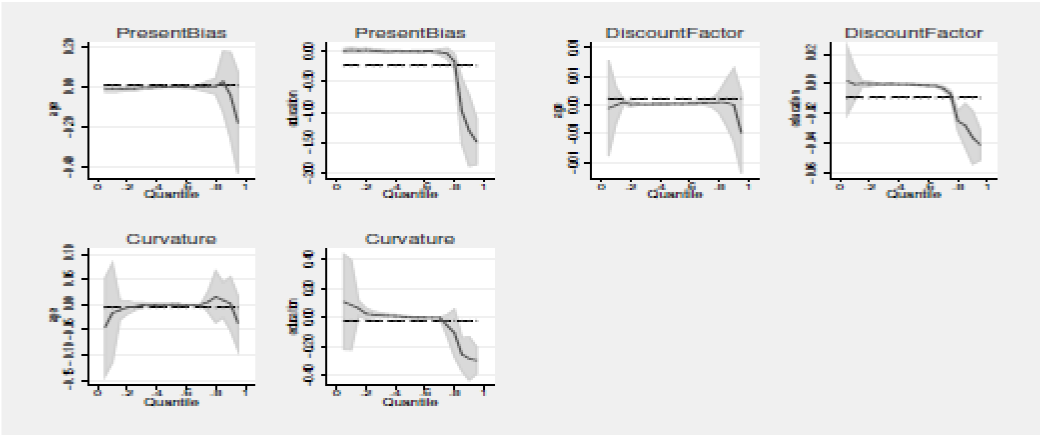
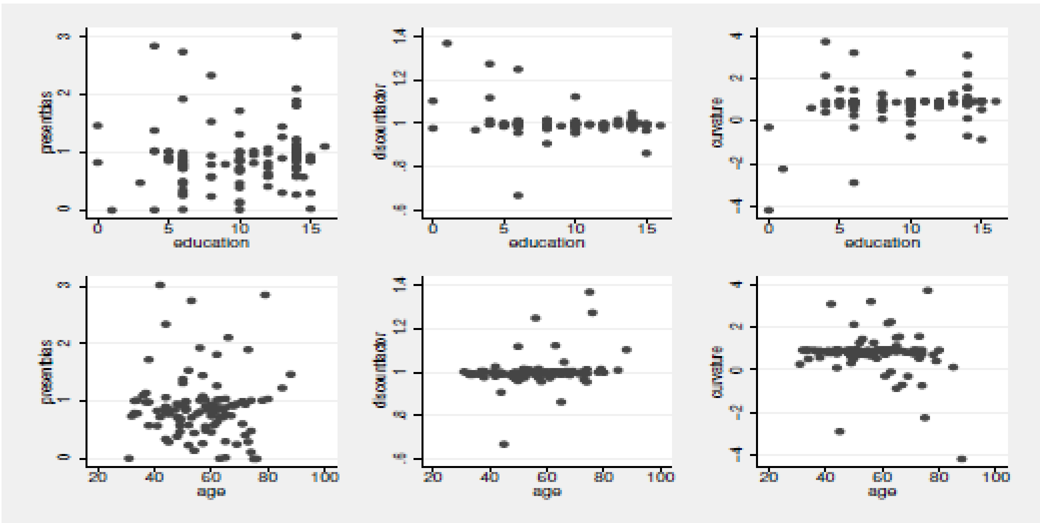



**Figure 2.5: The Relationship between Deep Parameters, Age and Education without Outliers**




We replicated the same analysis using a trimmed sample by deleting observations with the largest present bias parameter (Table 2.12). The results, shown in Table 2.13 and Figure 2.6, maintain the same qualitative pattern as before.

### Table 2.12: The Result in Individual CTB without Outliers

| Statistics | Present Bias | Discount Factor | Curvature |
|---|---|---|---|
| Count | 108 | 108 | 108 |
| Mean | 0.893 | 1.000 | 0.782 |
| sd | 0.540 | 0.066 | 0.916 |
| p5 | 0.119 | 0.960 | -0.704 |
| p25 | 0.599 | 0.990 | 0.745 |
| Median | 0.855 | 0.994 | 0.899 |
| p75 | 1.017 | 1.001 | 0.938 |
| p95 | 1.929 | 1.102 | 2.137 |

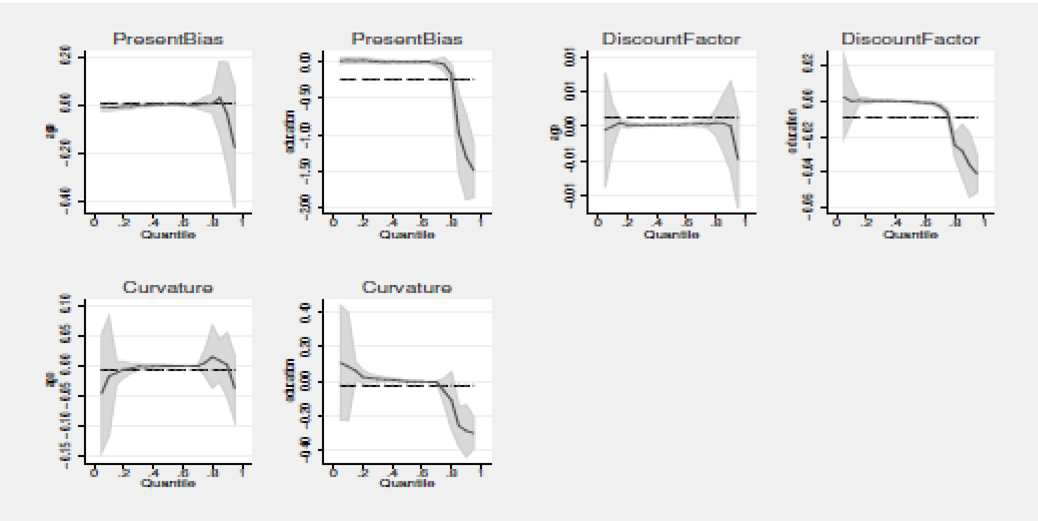
### Table 2.13: OLS Regression without Outliers

| | (1) presentbias | (2) discountfactor | (3) curvature |
|---|---|---|---|
| age | -0.000268 | 0.00108* | -0.0101 |
| | (0.00471) | (0.000515) | (0.00953) |
| education | 0.00538 | -0.00335 | 0.0462 |
| | (0.0144) | (0.00224) | (0.0329) |
| _cons | 0.856** | 0.973*** | 0.895+ |
| | (0.294) | (0.0340) | (0.453) |
| *N* | 108 | 108 | 108 |

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

### Figure 2.6: The Quantile Regression without Outliers



## 4.4 Dictator Game Results

In addition to the CTB and the DMPL experiments, we conduct a canonical dictator game experiment to elicit altruism. In the dictator game, the sender, called the "dictator," is provided with PhP 1,000 in 100 peso notes as the initial endowment that he/she can either keep or allocate to the receiver. Hence, the dictator must decide the transfer amount to his receiver from the possible transfer amounts, 0, 100, 200, 300, 400, 500, 600, 700, 800, 900, and 1,000 pesos. Since there is no self-interested reason for the sender to transfer money, the senders with zero transfers satisfy the Nash equilibrium. Hence, the actual positive amount of transfer is interpreted as the level of altruism (Camerer and Fehr, 2004; Levitt and List, 2007). We also adopt strategy methods, asking all participants as a sender the amounts they would send to each of four potential partners. The four partners are a randomly selected person in the same barangay, a randomly selected victim of the typhoon Yolanda, a randomly selected victim of the Great East Japan Earthquake of March 2011 and a randomly selected person from the Philippines. To investigate how the partner affects the subjects' responses and Habagat changes their responses, we postulate the following regression equation

$$Donation_{ij} = \beta_0 + \beta_1 Partner_{ij} + \beta_2 Habagat_i + \beta_3 Partner_{ij} \times Habagat_i + \beta_4 X_i + \varepsilon_{ij} \tag{13}$$

where $Donation_{ij}$ is the amount subject $i$ gives to the partner $j$ in the dictator game, $Partner_{ij}$ is a dummy variable which indicates who is the partner, $Habagat_i$ is a dummy variable which indicates whether the subject is affected by Habagat or not, $X_{ij}$ is a control variable and $\varepsilon_{ij}$ is an error term.

Histograms of the dictator game results are shown in Figure 2.7 by partner. The amounts sent to victims of typhoon Yolanda or the Great East Japan Earthquake are significantly larger than those sent to someone in the same village or in the Philippines. The same pattern is confirmed by the regression results of Table 2.14 and 2.15.

**Figure 2.7: The Histogram of the Amount of Donation**

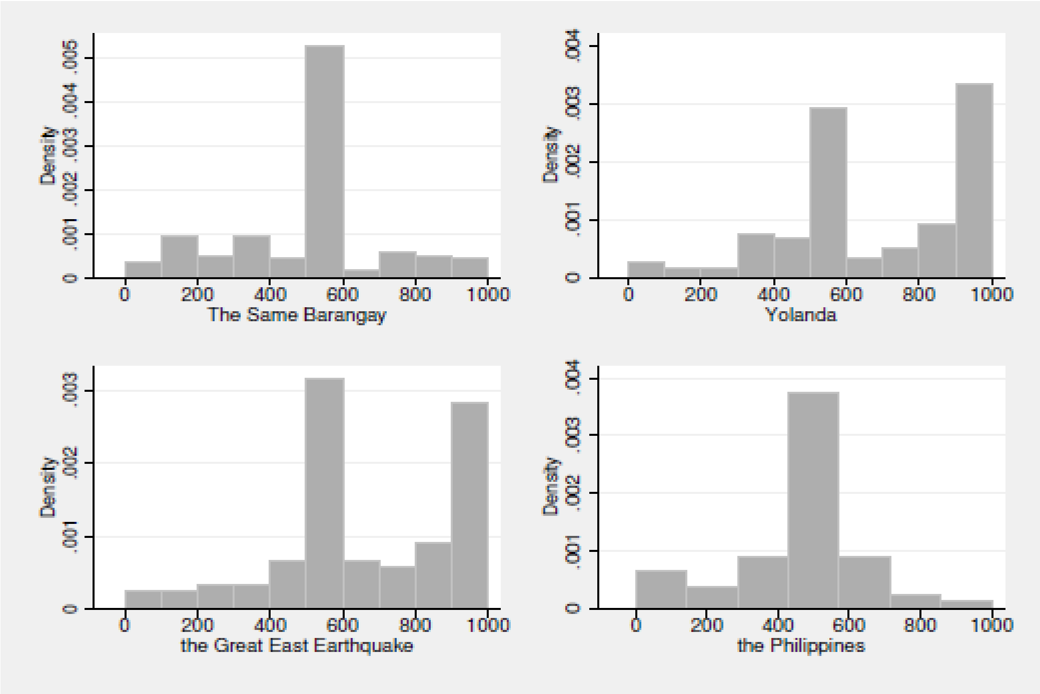


**Table 2.14: The Relationship between the Amount of Donation, the Partner and Habagat**

| | (1) donation | (2) donation | (3) donation | (4) donation | (5) donation |
|---|---|---|---|---|---|
| Yolanda | 195.8*** | 213.5*** | 213.5*** | 213.5*** | 145.7 |
| | (27.99) | (31.97) | (32.03) | (32.30) | (100.5) |
| Earthquake | 176.7*** | 187.6*** | 187.6*** | 187.6*** | 230.4* |
| | (27.77) | (33.48) | (33.53) | (33.82) | (95.18) |
| Philippines | -2.778 | 11.98 | 11.66 | 2.946 | 115.9+ |
| | (25.30) | (24.77) | (24.75) | (24.64) | (62.63) |
| gender | | -41.97 | -40.06 | -50.89 | -52.83 |
| | | (48.88) | (49.73) | (52.08) | (53.09) |
| age | | 6.870 | 7.469 | 11.45 | 11.06 |
| | | (11.60) | (12.01) | (11.39) | (11.90) |
| age2 | | -0.0233 | -0.0291 | -0.0610 | -0.0581 |
| | | (0.0954) | (0.0994) | (0.0941) | (0.0990) |
| education | | 10.91* | 10.60+ | 9.942+ | 10.11+ |
| | | (5.156) | (5.350) | (5.501) | (5.657) |
| None | | | -24.83 | | |
| | | | (89.64) | | |
| House | | | | -6.017 | 4.678 |
| | | | | (47.35) | (61.42) |
| Farm | | | | 9.752 | 0.308 |
| | | | | (47.30) | (63.87) |
| Assets | | | | -123.8 | -21.41 |
| | | | | (83.97) | (135.3) |
| Income | | | | 52.74 | 47.28 |
| | | | | (43.11) | (52.43) |
| Debt | | | | -9.620 | 9.281 |
| | | | | (43.09) | (56.69) |
| Sick | | | | -18.28 | -30.92 |
| | | | | (77.51) | (83.90) |

## Table 2.14: (*cont.*)

| | | | | | |
|---|---|---|---|---|---|
| House × Yolanda | | | | | -16.24 |
| | | | | | (72.77) |
| House × Earthquake | | | | | -37.03 |
| | | | | | (89.47) |
| House × Philippines | | | | | 15.50 |
| | | | | | (57.36) |
| Farm × Yolanda | | | | | 75.54 |
| | | | | | (81.98) |
| Farm × Earthquake | | | | | 1.740 |
| | | | | | (84.48) |
| Farm × Philippines | | | | | -89.12 |
| | | | | | (58.33) |
| Assets × Yolanda | | | | | -181.2 |
| | | | | | (181.2) |
| Assets × Earthquake | | | | | -195.0 |
| | | | | | (202.5) |
| Assets × Philippines | | | | | 170.2$^{+}$ |
| | | | | | (98.18) |
| Income × Yolanda | | | | | 66.37 |
| | | | | | (69.88) |
| Income × Earthquake | | | | | -10.18 |
| | | | | | (72.77) |
| Income × Philippines | | | | | -82.95 |
| | | | | | (56.56) |
| Debt × Yolanda | | | | | -18.72 |
| | | | | | (72.45) |
| Debt × Earthquake | | | | | -40.48 |
| | | | | | (76.78) |
| Debt × Philippines | | | | | 9.602 |
| | | | | | (61.70) |
| Sick × Yolanda | | | | | -80.61 |
| | | | | | (108.8) |

## Table 2.14: (*cont.*)

| | | | | | |
|---|---|---|---|---|---|
| Sick × Earthquake | | | | | 85.53 |
| | | | | | (109.5) |
| Sick × Philippines | | | | | 53.80 |
| | | | | | (78.24) |
| _cons | 458.3$^{***}$ | 32.29 | 43.86 | -114.2 | -111.0 |
| | (20.00) | (353.2) | (356.2) | (363.0) | (373.3) |
| $N$ | 414 | 307 | 307 | 307 | 307 |

Standard errors in parentheses

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

**Table 2.15: The Relationship between the Amount of Donation, the Deep Parameters, the Partner and Habagat**

| | (1)<br>donation | (2)<br>donation | (3)<br>donation | (4)<br>donation | (5)<br>donation |
|---|---|---|---|---|---|
| presentbias | -12.43$^{+}$ | -9.036 | -9.076 | -7.359 | -9.482 |
| | (6.614) | (8.642) | (8.649) | (9.236) | (8.650) |
| curvature | 9.596 | 4.993 | 5.128 | 2.432 | 5.534 |
| | (16.62) | (19.14) | (18.75) | (20.97) | (20.29) |
| discountfactor | 356.4$^{*}$ | 385.8$^{+}$ | 386.4$^{+}$ | 337.5 | 384.8 |
| | (145.1) | (217.3) | (217.5) | (255.6) | (250.4) |
| Yolanda | 213.5$^{***}$ | 213.5$^{***}$ | 213.5$^{***}$ | 213.5$^{***}$ | 145.7 |
| | (31.92) | (32.14) | (32.19) | (32.47) | (101.0) |
| Earthquake | 187.6$^{***}$ | 187.6$^{***}$ | 187.6$^{***}$ | 187.6$^{***}$ | 230.4$^{*}$ |
| | (33.42) | (33.65) | (33.70) | (33.99) | (95.71) |
| Philippines | 6.956 | 13.10 | 12.76 | 5.490 | 125.2$^{+}$ |
| | (27.25) | (25.05) | (25.06) | (24.63) | (64.88) |
| gender | | -50.99 | -48.89 | -50.12 | -52.83 |
| | | (49.58) | (50.37) | (52.57) | (53.63) |
| age | | 6.248 | 6.900 | 11.01 | 9.993 |
| | | (11.92) | (12.35) | (11.92) | (12.38) |
| age2 | | -0.0217 | -0.0280 | -0.0611 | -0.0531 |
| | | (0.0989) | (0.103) | (0.0994) | (0.103) |
| education | | 12.65$^{*}$ | 12.30$^{*}$ | 11.38$^{+}$ | 11.54$^{+}$ |
| | | (6.002) | (6.143) | (6.114) | (6.253) |
| None | | | -28.00 | | |
| | | | (90.93) | | |
| | | | | -13.27 | -1.671 |
| House | | | | (49.42) | (65.19) |
| Farm | | | | 8.266 | -0.926 |
| | | | | (47.95) | (66.25) |
| Assets | | | | -81.77 | 21.39 |
| | | | | (94.06) | (146.0) |

**Table 2.15: (*cont.*)**

| | | |
|---|---|---|
| Income | 47.95 | 42.31 |
| | (44.03) | (54.96) |
| Debt | -25.41 | -7.988 |
| | (45.42) | (59.13) |
| Sick | -27.44 | -40.27 |
| | (78.22) | (88.94) |
| House × Yolanda | | -16.24 |
| | | (73.17) |
| House × Earthquake | | -37.03 |
| | | (89.96) |
| House × Philippines | | 11.30 |
| | | (57.89) |
| Farm × Yolanda | | 75.54 |
| | | (82.43) |
| Farm × Earthquake | | 1.740 |
| | | (84.95) |
| Farm × Philippines | | -95.66 |
| | | (60.51) |
| Assets × Yolanda | | -181.2 |
| | | (182.2) |
| Assets × Earthquake | | -195.0 |
| | | (203.6) |
| Assets × Philippines | | $224.3^{+}$ |
| | | (127.3) |
| Income × Yolanda | | 66.37 |
| | | (70.27) |
| Income × Earthquake | | -10.18 |
| | | (73.18) |
| Income × Philippines | | -84.71 |
| | | (57.44) |
| Debt × Yolanda | | -18.72 |
| | | (72.85) |

**Table 2.15: (*cont.*)**

| | | | | | |
|---|---|---|---|---|---|
| Debt×Earthquake | | | | | -40.48 |
| | | | | | (77.20) |
| Debt×Philippines | | | | | 8.979 |
| | | | | | (62.33) |
| Sick×Yolanda | | | | | -80.61 |
| | | | | | (109.4) |
| Sick×Earthquake | | | | | 85.53 |
| | | | | | (110.1) |
| Sick×Philippines | | | | | 48.23 |
| | | | | | (81.45) |
| _cons | 85.11 | -339.0 | -326.0 | -429.0 | -454.6 |
| | (152.7) | (415.5) | (416.5) | (437.6) | (433.7) |
| *N* | 307 | 307 | 307 | 307 | 307 |

Standard errors in parentheses

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

## 4.5. Behaviours

In previous studies on behavioural economics, researchers attributed undesirable behaviours such as obesity, over-eating, debt overhang, gambling, smoking, drinking, and other procrastination behaviours to naive hyperbolic discounting (Banerjee and Mullainathan, 2010). In our data, we can verify whether and how individual preferences are related with risk taking behaviour such as gambling, smoking, and drinking. The estimation results are shown in Table 2.16, which represents insignificant relationship between the present bias parameter and risk taking behaviours.

**Table 2.16: The Relationship between Risk Taking Behavior and Deep Parameters**

| | (1) #ofgambling | (2) #ofgambling | (3) smoking | (4) smoking | (5) alcohol | (6) alcohol |
|---|---|---|---|---|---|---|
| presentbias ($\beta$) | 0.0470 | 0.0376 | -0.00530 | 0.00557 | -0.0246 | -0.0114 |
| | (0.0297) | (0.0284) | (0.0231) | (0.0213) | (0.0183) | (0.0165) |
| discountfactor ($\delta$) | -2.187** | -1.964* | 0.0641 | -0.187 | 1.258** | 0.0779 |
| | (0.685) | (0.808) | (0.894) | (0.845) | (0.420) | (0.581) |
| curvature ($\alpha$) | 0.0199 | 0.0341 | 0.0117 | -0.00588 | -0.0409 | 0.0125 |
| | (0.0602) | (0.0670) | (0.0580) | (0.0559) | (0.0347) | (0.0547) |
| gender | | -0.393* | | 0.371*** | | 0.517*** |
| | | (0.164) | | (0.0568) | | (0.0759) |
| age | | 0.0000458 | | 0.0199 | | -0.0285 |
| | | (0.0427) | | (0.0259) | | (0.0279) |
| age2 | | 0.000000240 | | -0.000153 | | 0.000316 |
| | | (0.000366) | | (0.000229) | | (0.000249) |
| education | | -0.00295 | | 0.00367 | | -0.0114 |
| | | (0.0215) | | (0.0106) | | (0.0108) |
| _cons | 2.876*** | 2.799+ | 0.682 | 0.172 | -0.680 | 0.956 |
| | (0.690) | (1.613) | (0.859) | (1.203) | (0.424) | (1.043) |
| $N$ | 120 | 120 | 120 | 120 | 120 | 120 |

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

## 5. Conclusion

This paper's empirical investigations provide three main results. First, the Convex Time Budget (CTB) experiments developed by Andreoni and Sprenger provide reasonable levels of present bias, time discounting and risk aversion parameters in all specifications. Second, in contrast with Andreoni and Sprenger's findings in the United States, we find that the estimated present bias parameter falls significantly below one in the Filipino village we studied, indicating quasi-hyperbolic discounting in the whole sample. This finding indicates that Andreoni and Sprenger's argument that the unique steps CTB experiments take to equate the costs and risks associated with payments that are made too soon and payments that are made too late may not be related to the dynamically consistent time preferences they obtain. Finally, we divide our sample into sub-groups depending on their damage types. By doing this, we find that the natural disaster affects the present bias parameter: being hit by the flood makes individuals significantly more present-biased than those who are unaffected by the flood. This implies that individual preference parameters are not constant over time and that they change under some circumstances.

These findings come with several important caveats. First, while we find that the natural disaster affects the present bias parameter, the mechanisms behind such affects are still unknown from the theoretical viewpoints. Second, since the relationship between preference parameters and real-world socio-economic circumstances are under-investigated, we should link and analyse living standard surveys and experimental responses by the same individuals. These are important tasks for future research.

## References


Andersen, S., G. W. Harrison, M. I. Lau and E. E. Rutström (2008), 'Eliciting Risk and Time Preferences', *Econometrica* 76(3), pp.583-618.

Andreoni, J. and C. Sprenger (2012), 'Estimating Time Preferences from Convex Budgets', *American Economic Review* 102(7), pp.3333-56.

Andreoni, J., M. Kuhn and C. Sprenger (2013), 'On Measuring Time Preferences', mimeographed, San Diego, CA: University of California.

Banerjee A. and S. Mullainathan (2010), 'The Shape of Temptation: Implications for the Economic Lives of the Poor', mimeographed, Cambridge, MA: MIT.

Callen, M., M. Isaqzadeh, J. D. Long, and C. Sprenger (2014), 'Violence and Risk Preference: Experimental Evidence from Afghanistan', *American Economic Review* 104(1), pp.123-48.

Camerer, C. and E. Fehr (2004), 'Measuring Social Norms and Preferences Using Experimental Games: A Guide for Social Scientists', in J. Henrich, R. Boyd, S. Bowles, C. Camerer, E. Fehr and H. Gintis (eds.), *Foundations of Human Sociality: Economic Experiments and Ethnographic Evidence from Fifteen Small-Scale Societies*. Oxford, UK: Oxford University Press, pp.55-95.

Cameron, L. and M. Shah (2012), 'Risk-Taking Behavior in the Wake of

Natural Disasters', *IZA Discussion Paper*, No. 6756, Bonn, Germany: Institute for the Study of Labor.

Cardenas, C. and J. Carpenter (2008), 'Behavioural Development Economics: Lessons from Field Labs in the Developing World', *Journal of Development Studies* 44(3), pp.311-38.

Cassar, A., A. Healy, and C. von Kessler (2011), 'Trust, Risk and Time Preferences after a Natural Disaster: Experimental Evidence from Thailand', mimeographed, San Fransisco, CA: University of San Francisco.

Fehr, E. and K. Hoff (2011), 'Introduction: Tastes, Castes and Culture: The Influence of Society on Preferences,' *Economic Journal* 121, pp.396-412.

Fuwa, N. (2011), 'Should We Track Migrant Households When Collecting Household Panel Data? Household Relocation, Economic Mobility and Attrition Biases in the Rural Philippines', *American Journal of Agricultural Economics* 93 (1), pp.56-82.

Hayami, Y. and M. Kikuchi (2000), '*A Rice Village Saga: Three Decades of Green Revolution in the Philippines*', London: MacMillan Press.

Holt, C. A. and S. K. Laury (2002), 'Risk Aversion and Incentive Effects', *American Economic Review* 92(5), pp.1644-55.

Kajisa, K. (2007), 'Personal Networks and Nonagricultural Employment: The Case of a Farming Village in the Philippines', *Economic Development and Cultural Change* 55(4), pp.699-707.

Levitt, S. and J. List (2009), 'Field Experiments in Economics: The Past, the Present, and the Future', *European Economic Review* 53(1), pp.1-18.

Sawada, Y., Y. Higuchi, K. Kajisa, N. Fuwa, E.B. Marciano and J.P. Estudillob (2012), 'The East Laguna Village: Four Decades of Studies in a Filipino Village', *PRIMCED Discussion Paper Series*, No. 18, Tokyo: Institute of Economic Research, Hitotsubashi University.

Stigler, G. J. and G. Becker (1977), 'De gustibus non est disputandum', *American Economic Review* 67(2), pp.76-90.

Umehara, H. (1967), 'Philippine no Beisaku Noson' (in Japanese: A rice village in the Philippines), in T. Takigawa and H. Saito (eds.), *Ajia no Tochi Seido to Noson shakai kozo* (Land Tenure System and Rural Social Structure in Asia), Tokyo: Institute of Developing Economies.

Voors, M. J., E. E. M. Nillesen, P. Verwimp, E. H. Bulte, R. Lensink, and D. P. van Soest (2012), ‘Violent Conflict and Behavior: A Field Experiment in Burundi’, *American Economic Review*102(2), pp.941-64.