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On the Stability of Preferences: Experimental Evidence from Two Disasters

Yusuke Kuroishi
London School of Economics
Yasuyuki Sawada
The University of Tokyo
and AsianDevelopment Bank

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Yusuke Kuroishi* Yasuyuki Sawada‡

Abstract

The literature concerning how preferences are affected by extreme events is characterized by mixed findings. To bridge this gap, we investigate the impacts of two disasters triggered by different natural hazards on present bias, exponential time discounting, and curvature parameters of a utility function. These are elicited in an integrated manner by the convex time budget (CTB) experiments as well as the multiple price list (MPL) experiments. Based on these approaches, we employ sui generis experimental data and accurate disaster damage information from the official metrical surveys in Iwanuma city of Japan and from satellite images of the East Laguna Village of the Philippines, which were hit, respectively, by a strong earthquake and tsunami in 2011 and serious floods in 2012. First, we find that disaster exposure makes individuals more present-biased and less risk-averse regardless of distinctive differences in socio-economic conditions and disaster types. Second, the impact lasted for 6 years in both areas, suggesting persistency of the effect. Third, our results are consistent with emotional channels but not necessarily with a potential market friction in the form of binding liquidity constraints. Our findings suggest that the existing mixed empirical evidence can be attributed to the lack of an integrated and consistent framework as well as accurate data on disaster damages, rather than variations in literacy or education levels of experimental subjects.

*London School of Economics, E-mail: yusukekuroishi@gmail.com

†Facity of Economics, University of Tokyo, E-mail: sawada@e.u-tokyo.ac.jp; Chief Economist, Asian Development Bank, E-mail: ysawada@adb.org

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1 Introduction

The literature on the endogenous formation of individual preferences reveals that these preferences are not constant across time and change under some circumstances (Fehr and Hoff (2011); Chuang and Schechter (2015)). Since natural hazards and man-made disasters are traumatic events, exposure to them are likely to affect an individual's preference and behavior. While many recent studies have investigated how preferences are affected by these extreme events, their findings are mixed and inconclusive (Chuang and Schechter (2015) and Schildberg-Hörisch (2018)). For example, Cameron and Shah (2015) and Cassar et al. (2017) consider the cases of Indonesia and Thailand, respectively, finding that exposure to natural hazards make people more risk-averse. However, findings of Hanaoka et al. (2018) on an earthquake in Japan, Page et al. (2014) on floods in Australia, and Voors et al. (2012) on civil war in Burundi show that victims become less risk-averse systematically. Moreover, Callen et al. (2014) find no change in risk aversion for those exposed to insurgency attacks in Afghanistan. Concerning time discounting, while Callen (2015) finds that the Asian tsunami disaster in 2004 decreased impatience in Sri Lanka, it increased impatience in Thailand (Cassar et al. (2017)).

This study aims to close the aforementioned gap in the literature on the nexus between disasters and preferences. Particularly, we focus on the following two unresolved lacunae in the existing studies. First, there could be specification errors in estimation (Vieider (2018)). While the underlining economic model requires the incorporation of both risk and time preferences simultaneously (Andreoni and Sprenger (2012); Andersen et al. (2008); and Cheung (2016)), to the best of our knowledge, studies on the nexus between disasters and preferences do not consider joint inference of all parameters that collectively guide an individual's choices.[1] Additionally, a failure to consider possible market frictions, such as binding liquidity constraints, can bias the estimated parameters (Carvalho et al. (2016)).

Second, inaccurate data on disaster exposure and experimental results can generate systematic biases in estimating the impact of disasters on preferences, making it difficult to identify the causal relationship precisely (Chuang and Schechter (2015); Vieider (2018); Schildberg-Hörisch (2018)). For example, disaster exposures and damages can be inaccurately captured because of subjective reporting bias (Higuchi et al. (2019)) or due to data unavailability on individual-level disaster exposure (Hanaoka et al. (2018)). Additionally, noisy experimental results can distort estimation results if data quality is systematically correlated with literacy, education, and cognitive capacity of the subjects (Andersson et al. (2016); Chuang and Schechter (2015) and Schildberg-Hörisch (2018)).

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

Similarly, 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 different types of losses are not distinguished properly.

To bridge these gaps in the literature, we investigate the impact of two distinct natural disasters on present bias, exponential time discounting, and curvature parameters, that is, the intertemporal elasticity of substitution and the degree of risk aversion of a utility function. These are elicited in an integrated manner by considering an explicit joint determination explicitly through the following two incentivized experiments: the convex time budget (CTB) experiments developed by Andreoni and Sprenger (2012) and Andreoni et al. (2015) and the multiple price list (MPL) experiment developed by Andersen et al. (2008).

Based on these two frameworks, we conducted lab-in-the-field experiments in Iwanuma city of Japan, which was hit by a strong earthquake and tsunami in 2011, and in a village in the Philippines called the East Laguna Village,[2] which was affected by serious floods triggered by the monsoon Habagat in 2012. These experiments were conducted twice in both areas, around 2 years and 6 years after each disaster. An accurate information on the damage, which was collected from government metrical surveys in Iwanuma city and from satellite images in the East Laguna Village, and our sui generis datasets, which cover different disaster events in distinct settings in terms of age, income, and educational profiles of subjects (Figures 1, 2, and 3), allow us to investigate whether and how the effect of a disaster on deep parameters tends to be long-lasting and ubiquitous.

Our analysis leads to the following three findings. First, with the application of the two experimental methods on the two distinctive disasters show that disaster exposure makes individuals more present-biased and less risk-averse commonly in the two locations despite of their very different socio-economic characteristics. Second, we find that this impact persisted at least for 6 years in both countries. Third, robustness analyses suggest that our results are not driven by variations in the educational level of subjects. Conversely, our results are theoretically consistent with the emotional channel of the disaster's effect on preferences emphasized by Callen et al. (2014) and Hanaoka et al. (2018), which can be explained theoretically by a model of Chakraborty et al. (2019) but not necessarily with a potential market friction, in the form of binding liquidity constraints. These findings suggest that the mixed empirical evidence in the existing studies are driven by the lack of an integrated and consistent framework as well as inaccurate data on disaster damages.

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. In Section 6, we examine possible mechanisms behind our

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

findings. Section 7 presents the concluding remarks.

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 by strong floods in 2012. These two areas are characterized distinctively because subjects from these two communities are distributed very differently in terms of age (Figure 1), income (Figure 2), and educational level (Figure 3).

2.1 The Great East Japan Earthquake

Concerning the data from Japan,[3] we use 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),[4] together with additional data we gathered from two rounds of the lab-in-the-field experiment conducted in Iwanuma city. From July 2010 to January 2012, large-scale JAGES surveys were conducted with 169,215 community-dwelling individuals aged 65 years or above residing in 31 municipalities of 12 Japanese prefectures. 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 2,766 homes were either destroyed or seriously damaged by the earthquake and the resulting tsunami.[5]

Unlike typhoons, epidemics, and man-made disasters, tsunamis and floods present a clear "discontinuous" variation of local damages in a homogenous area with an unknown disaster border before the disaster, providing random assignments of "treatment" and "control" groups of disaster damages. We exploit this natural experimental situation to identify

[3]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 (Sawada (2013)). The continuous earthquake 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.

[4] 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.

[5]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.

causal impacts of disasters on individual preferences. Of the all 2013 JAGES census respondents in Iwanuma city, 1,023 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. Eventually, a total of 186 individuals participated in our field 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]

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.[8]

Besides its exposure to several natural hazards in the last decade (Sawada et al. (2009), Estudillo (2013)), in August 2012, the village was unexpectedly hit by serious out-of-season floods due to the southwest monsoon winds called "Habagat."[9] In the village data sets covering the last five decades, there has been no record of other floods at this scale.

[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] We conducted a series of experiments on the following dates in 2017: 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).

[8] The earliest documented survey of the village dates back to 1966, when a Japanese geographer, Hiromitsu Umehara, reported 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), Sawada et al. (2012)). 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); Sawada et al. (2012)). The village has been repeatedly surveyed, which has led to the collection, compilation, and analyses of useful benchmark information.

[9] Over an eight-day period, from August 1 to August 8, 2012, torrential rains and thunderstorms hit the Philippines. Its 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, in 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

In the East Laguna village's study, we employ the same type of survey and experiments as the ones adopted for Iwanuma city. The subjects comprised farmers in the East Laguna village and the two surrounding villages. Of the 200 farmers, in 2014, a total of 158 farmers participated in our field experiments.[10] Of the 161 farmers, in 2018, a total of 141 farmers participated in our field experiments.[11]

3 Parameter Estimation Strategies

We employed Andreoni et al. (2015)'s CTB experiment 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), and Laibson (1997))—the intertemporal elasticity of substitution, α; the exponential time discounting factor, δ; and the quasi-hyperbolic discounting factor showing present-biasness, 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 $\beta < 1$, $\beta = 1$ corresponds to the case of standard exponential discounting.

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, 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 in each experimental session. The experiments in Iwanuwa were organized with full endorsement by Iwanuma city government which

6,000 farmers in the whole area. More than a half of the village area was submerged in flooded water, destroying paddy seriously.

[10] 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).

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

was stated in the invitation letters and 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 five 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 rate.[12] 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:

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

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.[13] 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 at these corner solutions. 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:[14]

$$x_t = \frac{Y(\beta^{t_0}\delta^k P)^{-\frac{1}{\alpha}}}{1 + P(\beta^{t_0}\delta^k P)^{-\frac{1}{\alpha}}}. \tag{2}$$

.

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

[13]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.

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

3.2 The Multiple Price List (MPL) Experiment

The second experiment is the MPL experiment of Andersen et al. (2008), which 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.[15] As for delayed payments, we arranged in the same way as the CTB experiments explained beforehand.

In this experiment, we also assume a time separable CRRA utility function: $U(x) = \frac{x_t^{1-\tilde{\alpha}}}{1-\tilde{\alpha}} + \beta \sum_{k=1}^{\infty} \delta^k \frac{x_{t+k}^{1-\tilde{\alpha}}}{1-\tilde{\alpha}}$ where $\tilde{\alpha}$ represents the coefficient of the relative risk aversion in this experiment.[16] As in the CTB experiment, the parameter δ captures the standard long-run 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)):

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

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

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

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 time preference MPL, 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:

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

[16] With this functional form, $\tilde{\alpha} = 1$ denotes the risk-neutral behavior, $\tilde{\alpha} < 1$ denotes risk aversion, and $\tilde{\alpha} > 1$ denotes risk tolerance.

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

However, the present value of choosing the larger delayed payment, PV_Y, is

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

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

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

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 these two conditional log-likelihood functions (5) and (9) 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:

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

which is maximized using standard numerical methods.

4 Empirical 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 Baseline Covariate Balance Test

In Iwanuma city, local governments conducted detailed metrical surveys of damages and issued official damage certificates for each house, with which households could obtain government compensations and reallocation of donations. We obtain the damage certificate data from 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 almost or totally collapsed. To check the exogeneity of damages, we regress each respondent's household's pre-disaster characteristics on these three variables, depicting different damage levels with the no damage group as a reference category.[17] According to Table 1, the joint test results show that each household's characteristics are not systematically correlated with the damage level, for subjects in both 2014 and 2017 experiments. These findings support our presumption that the earthquake provides a natural experimental situation that allows us to elicit the causal effect of the disaster on households' preferences.

4.2 The CTB Experiment Results

While the estimated quasi-hyperbolic discount factor is very close to one in the aggregate CTB estimation results of homogenous parameters,[18] we estimate the model of equation (1) by allowing a heterogenous 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. The results are shown in Table 2. As house damages become more severe, subjects show more present-biasness, both in 2014 and 2017. In

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

[18] Table 4 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 equation (3) using OLS and the last column shows results based on equation (4) using NLS. There are several differences between the results in 2014 and those in 2017. First, in all specifications of Table 4, we cannot reject the null hypothesis in which the present bias parameter, β, in the 2014 data. However, the estimated present bias parameter statistically falls below one in 2017, ranging from 0.976 to 0.983. Second, both results in 2014 and 2017 show that the exponential time discounting parameter, δ, is within a reasonable range. Indeed, the estimated daily discount factor shows that subjects devalue the utility of future consequences by 0.5 % to 0.6 %. Finally, the intertemporal substitution parameter, α, in 2014 and 2017, ranges from 0.718 and 0.853. These parameters are significantly different from 1 but closer to linear utility than other existing studies (Andreoni and Sprenger (2012) and Andreoni et al. (2015)).

fact, with "almost or totally collapsed home damage" caused by the disaster, β decreases from 1.057 to 0.937 in 2014 (column (1)) and from 1.045 to 0.893 in 2017 (column (4)). We reject the null hypotheses 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. Exposure to house damages caused by the Great East Japan Earthquake in 2011 seems to make people more present-biased consistently in both 2014 and 2017. The pooled as well as the balanced panel data confirm the finding that the disaster's effect on the present-biasness persisted at least for 6 years.[19]

4.3 The MPL Experiment Results

With experimental data in 2017, we also estimate the MPL model by allowing heterogenous parameters, depending on the degree of the house damage (Table 3).[20] We find that house damages make people more present-biased. 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.

5 Empirical 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." Subse-

[19]These results are shown in Online Appendix (Table A.8).

[20]The estimation results using the MPL and Holt and Laury (2002) are shown in the Online Appendix. Table 12 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.), 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.

quently, 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 Baseline Covariate Balance Test

The flood's damage levels are captured objectively and subjectively. Concerning the objective damage information, we employ the satellite images, which identifies whether households suffered farm-level damages due to the submergence of paddy fields by the flood. By comparing two 5 km by 5 km images taken by IKONOS before (May 23, 2012) and after (August 11, 2012) the floods, shown by Figure 4, we can identify the flood border shown by the red line of the Figure 5. Subsequently, we can define an indicator variable of flood damage, "Satellite Flood Damage," which takes one if a subject's farm is affected by the floods, and zero otherwise. 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, we could obtain 99 and 91 observations, respectively, in 2014 and 2017.

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. We define a binary variable of subjective flood damage, "Severity," by taking 1 if a subject suffered from at least three kinds of damages, out of the above mentioned six subjective damage categories, and 0 otherwise. The third damage variable, "Severity with Satellite Flood Damage," is an indicator variable based on the subjective and objective reports, which takes 1 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. It must be noted that the second and third measures, "Severity" and "Severity with Satellite Flood Damage," vary depending on the use of subjective farm damage data in case of the former or satellite-based objective farm damage in case of the latter. However, we can verify that the data pertaining to these two farm damages are largely consistent, by checking Figure 5 in which we overlaid the data on self-reported flood water depth on a post-flood satellite image with five categories: lightest blue (below ankle depth <10cm), light blue (below knee depth <40cm), blue (below hip depth <80cm), dark blue (below chest depth <120cm), and darkest blue (above chest depth >120cm).

Based on these three defined variables, 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 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 each one of the three damage variables.[21] Table 4 and Table 5 show, respectively, based on 2014 and 2018 data, that the pre-disaster characteristics of each household are not systematically correlated with the damage level. These results validate our empirical strategy to use the flood as a natural experiment, allowing us to elicit the causal effect of the flood damage on subjects' preferences.

5.2 The CTB Experiment Results

In order to examine the impact of the floods, we estimate the model by allowing the heterogenous curvature parameter, α; exponential time discounting parameter, δ; and the present bias parameter, β, depending on each of the damage categories we defined, "Satellite Flood Damage", "Severity," or "Severity with Satellite Flood Damage," where the parameter for those who suffered from the floods is indicated by subscript "1" and those who were unaffected is indicated by subscript "0." [22]

The estimation results in Table 6 show that $\beta_1 < \beta_0$ uniformly, indicating that exposure to the disaster reinforced people's present-biasness. The overall joint test results also support this tendency—in four out of six specifications, the difference between β_1 and β_0 is statically significant at the 10% level. In contrast, other parameters, α and δ, are 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 7 and 8 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. While statistical significance is seen to be marginal for the specifications when using the "Satellite Flood Damage" variable, we consistently observe that flood damages make respondents present-biased. Additionally, we find that, with flood damage, subjects become more risk-tolerant with declined coefficient of relative risk aversion, $\tilde{\alpha}$. Qualitatively, these results

[21] 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.

[22] Table 5 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.

are comparable to the ones we obtain from the Japanese data.[23]

6 Possible Mechanisms

Why do disasters make people more present-biased? To approach this question, we follow existing studies to consider two possible channels for the nexus between disaster and present biasness. While direct income and asset losses may cause preference changes, the existing studies such as Haushofer and Fehr (2014) reveal that a decrease in resources can lead to short-sighted and risk-averse decision-making, highlighting importance of psychological channels. Since our experimental results indicate that disaster victims become less risk-averse, not more risk-averse, there could be peculiar psychological impacts generated by exposure to extreme events.

Accordingly, we first consider emotional channel based on the existing laboratory experiments in psychology which show that emotional responses to negative shocks, such as fear, may affect risk attitudes (Callen et al. (2014); Hanaoka et al. (2018)). Also, "scarcity" can impede one's cognitive functions, leading to seemingly myopic behaviors (Mani et al. (2013)).[24]

Second, economic losses may affect preferences directly: Scarcity of monetary resources or simply binding liquidity constraints can also make people seemingly present biased (Carvalho et al. (2016)). Here, we examine these two possible intervening variables, that is, emotion and liquidity constraints.

6.1 The Emotion Channel

After people are exposed to the disaster, they emotionally orient their beliefs on their survival by decreasing survival probability. As a result, their intertemporal marginal rate of substitution increases only at the current period, unchanging the rates for the future periods. Therefore, those who suffered damages caused by the disaster choose early payments

[23] Table 17 show 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

[24] In general, scarcity consumes attentional resources, leading to particular decisions. However, losing financial resources, physical assets, and family members can consume attentional resources in a differentiated manner, leading to distinctive biases on cognitive function.

when compared to those who were unaffected, and this is consistent with the result that they show more present biasness. This mechanism is also explained in detail through a theoretical model of Chakraborty et al. (2019).

We examine this emotional channel empirically by using additional information available from our two datasets. In the JAGES data from Japan, we can employ questions on three binary variables taken from the clinically-validated $K6$ measure of depression of Kessler et al. (2002): First, "Desperate Feeling" takes 1 when the respondents feel that their lives are desperate and 0 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 house damage variables. The results are shown in Table 9 for 2014 and 2017. We can see that disaster exposure make subjects feel more "Desperate" and "Hopeless" persistently even after six years, supporting the emotional channel.

During the 2018 experiments in the Philippines, we included a question asking whether the subjects perceive a decline in their life expectancy after the floods in 2012. According to the result reported in Table 10, individuals exposed to the floods perceived a decline in their life expectancy. Overall, results seem to be consistent with the persistent emotional channel.

6.2 The Liquidity Constraint Channel

Alternatively, damages may make people seemingly present biased by reinforced liquidity constraints due to economic losses.[25] If subjects face liquidity constraints, then their Euler equation in the CTB method would take the following form:

$$u'(c_t) = \beta\delta^k(1+r)u'(c_{t+k}) + \lambda_t \quad if \quad t = 0, \tag{11}$$

$$u'(c_t) = \delta^k(1+r)u'(c_{t+k}) \quad if \quad t \neq 0, \tag{12}$$

where λ_t is the Lagrange multiplier associated with the liquidity constraint (Zeldes (1989)). If a disaster reinforces the current liquidity constraint, then λ_t should be larger, leading to a lower β to satisfy the above equation. To check this channel, we postulate the CRRA utility $u(c_t) = \frac{c_t^{1-\alpha}}{1-\alpha}$ and combine the previous two results:

$$c_t^{-\alpha} = \beta^{\mathbb{1}(t=0)}\delta^k(1+r)c_{t+k}^{-\alpha} + \mathbb{1}(t=0)\lambda_0, \tag{13}$$

[25] Carvalho et al. (2016) 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.

where $\mathbb{1}(t=0)$ is an indicator function, which takes 1 if t=0 and 0 otherwise. Rearranging this, we obtain the following non-linear regression form:

$$ln(c_t) = \frac{1}{-\alpha} ln(\beta^{\mathbb{1}(t=0)} \delta^k (1+r) c_{t+k}^{-\alpha} + \mathbb{1}(t=0)\lambda_0). \tag{14}$$

While we do not observe the values of λ_0 directly, we employ the following tractable specification of λ_0:

$$\lambda_0 = \tau_0 \mathbb{1}(\text{LC}) + \tau_1 \mathbb{1}(t=0)\mathbb{1}(\text{LC}) INC. \tag{15}$$

where $\mathbb{1}(\text{LC})$ is an indicator function, which takes 1 when a subject faces a liquidity constraint and zero otherwise, and INC is annual income. According to Zeldes (1989), our theoretical predictions are $\tau_0 > 0$ and $\tau_1 < 0$.

In the case of Japan, no respondent in the JAGES survey claimed frequent money shortage for food purchases, indicating that liquidity constraints were not binding among 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 follow Equations (14) and (15) and re-estimate the preference parameters only for the Philippines by using the CTB data and the annual business profit data as proxies of income, allowing for the existence of a liquidity constraint.

The results reported in Table 11 and Table 12 for 2014 and 2018, respectively show that the estimated parameters related to the liquidity constraint, that is, τ_0 and τ_1, are consistent with our theoretical prediction based on the consumption Euler equation with liquidity constraints. However, the estimated β is still systematically lower for those exposed to the floods than those not exposed. This suggests that the inclusion of the liquidity constraint cannot fully explain the reinforced present biasness by a disaster. Our overall results are in favor of the emotional channel, rather than the liquidity constraint channel.

As a by-product, we also find that the estimated β becomes smaller uniformly once we incorporate the liquidity constraints into the estimation model. This could be seen consistent with Carvalho et al. (2016) which finds seeming presentbiasness among those who face liquidity constraints if allowing heterogenous behavioral response to binding liquidity constraints in the estimation model.

7 Site-Selection Bias

Individuals who agree to participate in our experiments may be systematically different from the rest of the population. When the probability of a person's participation in experiments is correlated with outcomes of experiments, there will be site selection bias in estimating impacts of disasters (Allcott (2015), Banerjee et al. (2017)). To check existence of such bias, we apply the standard Heckman sample selection correction procedure to the JAGES census data from Iwanuma city. Specifically, we estimate the probability of participation in experiments jointly with the main Euler equation for the CTB experiments, i.e., Equation (1), by the maximum likelihood method under the joint normality assumption. The estimation results are reported in Table 13. While the estimated covariance between the error terms in the first and second stage models are negative and statistically significant, indicating that there is non-random selection, qualitative results for both 2014 and 2017 experimental data are maintained even if we make correction for potential site-selection bias. These results suggest that site-selection bias is not necessarily problematic in our settings.

8 Concluding Remarks

To explain the existing mixed empirical results on the nexus between disaster and preference in a consistent manner, we adopted the CTB and the MPL experiments and employed accurate damage information from official metrical surveys and satellite images. We find that disaster exposure makes individuals more present-biased and less risk averse, persistently and systematically, among two distinct sets of subjects in Japan and the Philippines with different age, income, and education levels. Our results are largely consistent with Callen et al. (2014) and Hanaoka et al. (2018), supporting the emotional channel behind the nexus between disasters and preference. These findings suggest that the existing mixed evidence can be attributed to the lack of an integrated and consistent framework and inaccurate data on disaster damages, rather than variations in literacy or education levels of experimental subjects because our qualitative results are consistent in Japan and the Philippines despite of large differences in education levels, income, and age.

The literature on hyperbolic discounting attributes harmful behaviors, such as obesity, over-eating, debt overhang, gambling, smoking, drinking, and other procrastination behaviors, to naive hyperbolic discounting (Banerjee and Mullainathan (2010)). Indeed, our companion study reveals that present biasness reinforced by disasters induce unhealthy behaviors such as over-eating, 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. (2018)). Hence, our study also sheds a new light on post-disaster rehabilitation policies by highlighting the importance of providing commitment devices to disaster victims for mitigating negative behavioral consequences of reinforced present-biasness, in line with Dupas (2011), Giné et al. (2010), and Bryan et al. (2010).

Moreover, the recent experimental literature on hyperbolic discounting focuses on the difference between the domain of monetary choice and the domain of 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 fully based on monetary choices may underestimate the true impacts of disasters on real-world behavior. In any case, to check the external validity of our study's findings, further investigations on the impact of disasters on individual preferences should be conducted for other disaster events in a systematic manner.

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Figure 1: Comparison of Age levels

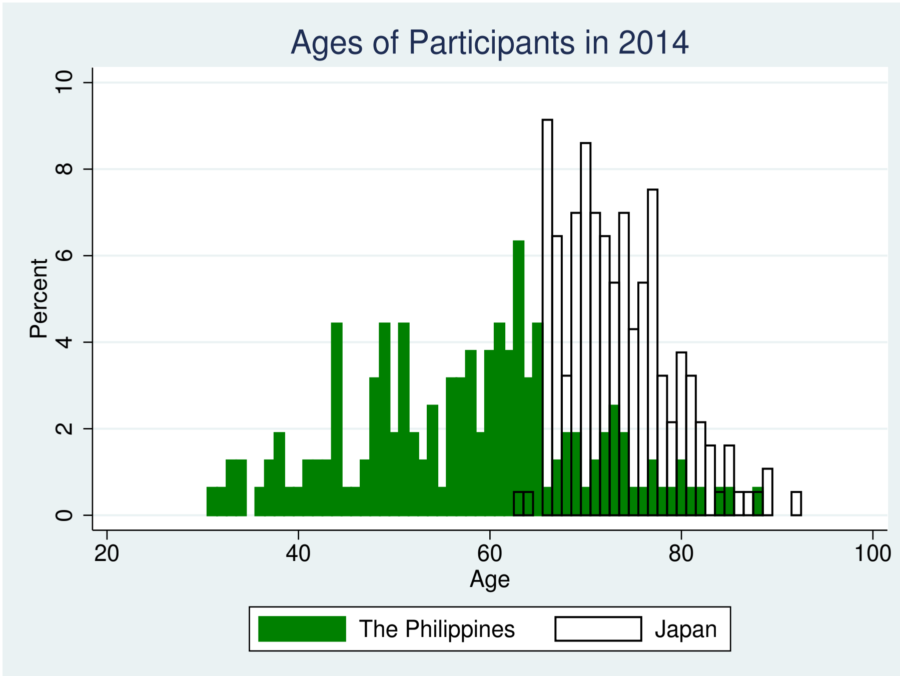


Figure 2: Comparison of Income Levels

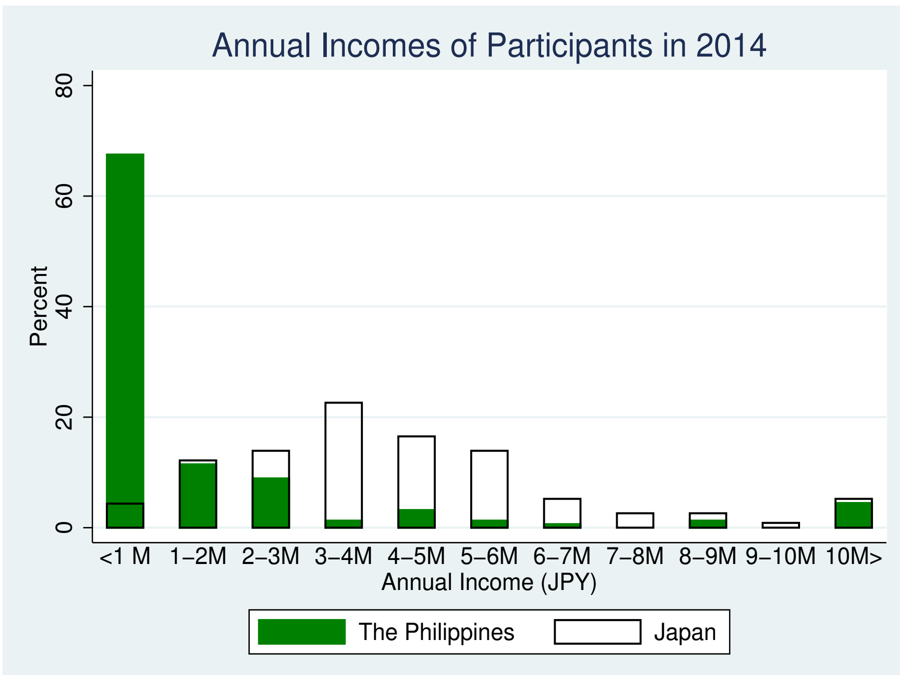


Figure 3: Comparison of Education levels

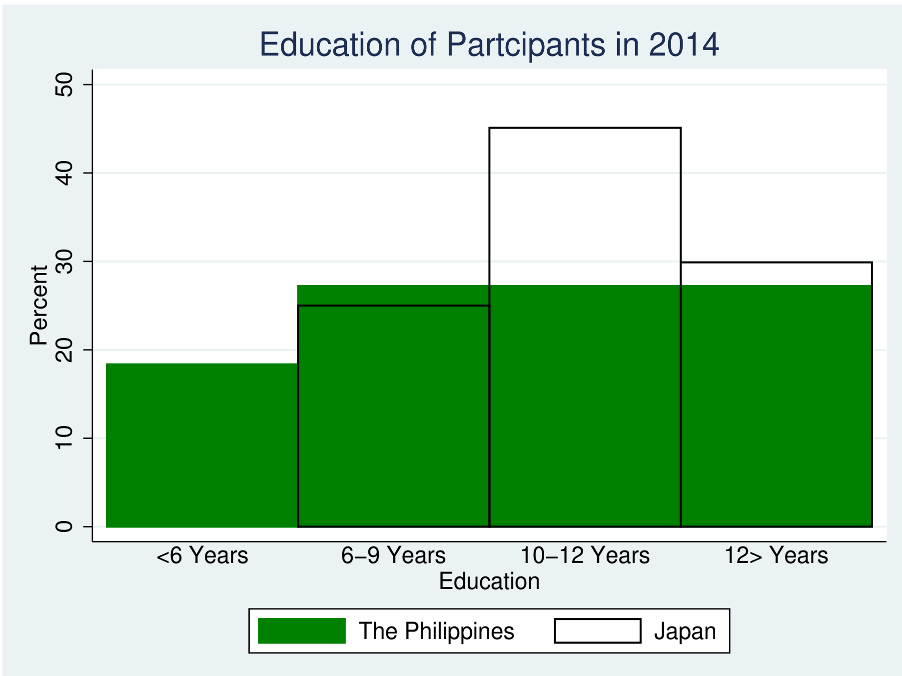


Figure 4: The Satellite Images of the East Laguna Village (May 23, 2012 and August 11, 2012)

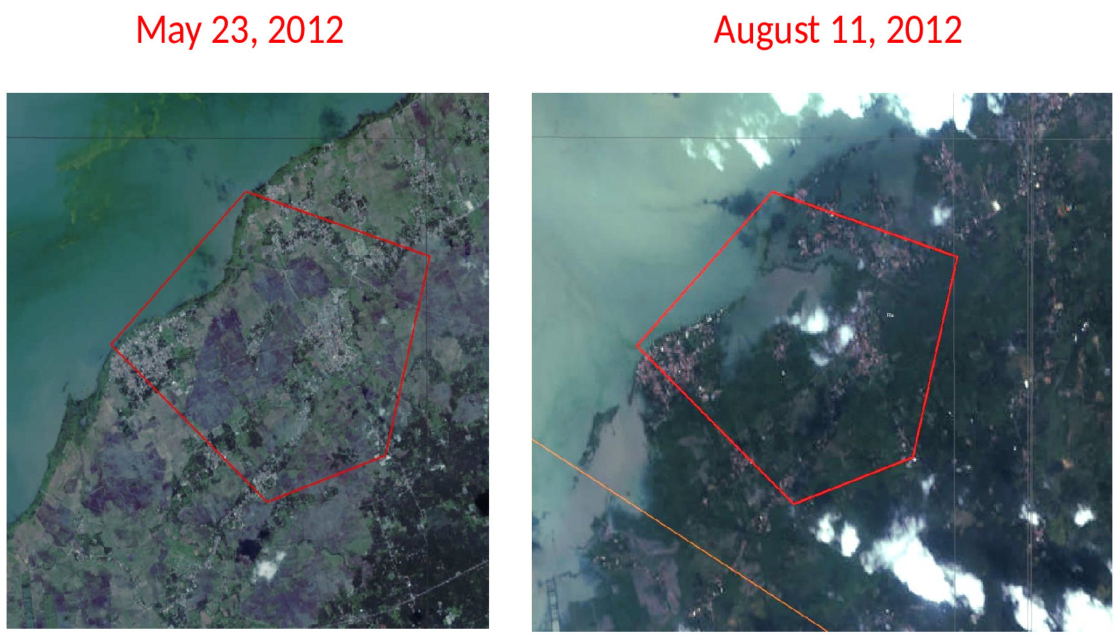
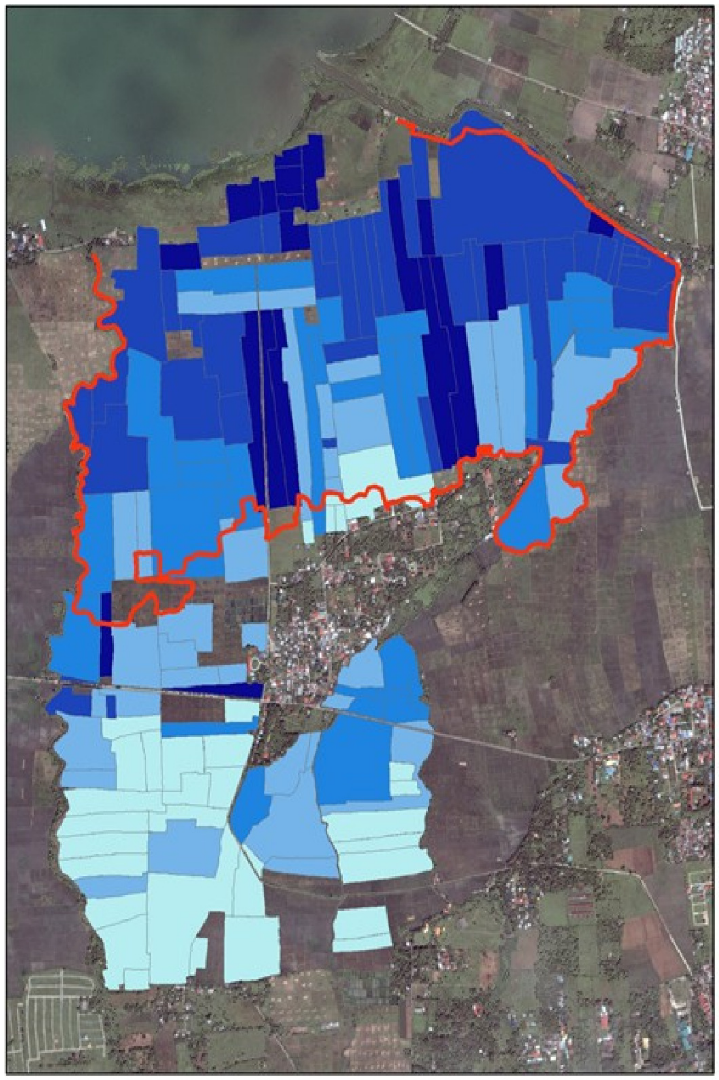


Figure 5: The Satellite Image of Farms



Notes: The data on self-reported water depth is overlaid on the satellite image with five categories: lightest blue (below ankle depth <10cm), light blue (below knee depth <40cm), blue (below hip depth <80cm), dark blue (below chest depth <120cm), and darkest blue (above chest depth >120cm).

Table 1: Covariate Balance Test in Japan (2014 and 2017)

	Subjects in 2014										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
VARIABLES	Age	Education	Job	Insurance	Own House	House Size	Loan Dummy	Years of Loan	BMI	Drinking	Smoking
With Minor or Half-damaged House	0.821	-0.00362	0.0560	-0.119	0.100	5.546	-0.0815	-1.249	0.740	-0.0453	-0.0274
	(1.002)	(0.0552)	(0.0773)	(0.0887)	(0.0610)	(3.991)	(0.0659)	(1.065)	(0.580)	(0.108)	(0.111)
With Almost or Totally-collapsed House	-1.217	-0.124	0.0993	-0.117	0.119*	13.89*	-0.0376	-1.037	1.335	0.102	0.0179
	(1.090)	(0.0817)	(0.0983)	(0.108)	(0.0657)	(7.656)	(0.0821)	(1.175)	(0.835)	(0.141)	(0.154)
Constant	73.32***	0.894***	0.234***	0.553***	0.830***	37.57***	0.191***	2.319**	22.46***	0.621***	0.607***
	(0.795)	(0.0453)	(0.0623)	(0.0731)	(0.0553)	(3.287)	(0.0579)	(0.985)	(0.460)	(0.0913)	(0.0935)
P-value of the joint zero hypothesis	0.110	0.248	0.584	0.377	0.182	0.143	0.433	0.503	0.231	0.483	0.933
Observations	186	186	186	185	186	186	186	186	117	120	113

	Subjects in 2017										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
VARIABLES	Age	Education	Job	Insurance	Own House	House Size	Loan Dummy	Years of Loan	BMI	Drinking	Smoking
With Minor or Half-damaged House	-0.0704	0.0391	0.0803	-0.0930	0.0652	1.970	-0.103	-1.103	0.469	-0.131	-0.241**
	(0.909)	(0.0565)	(0.0784)	(0.0879)	(0.0618)	(4.507)	(0.0653)	(0.921)	(0.564)	(0.103)	(0.0993)
With Almost or Totally-collapsed House	-1.163	-0.0218	0.0881	-0.144	0.0929	7.503	-0.105	-1.060	0.880	0.110	-0.194
	(1.081)	(0.0748)	(0.0967)	(0.105)	(0.0675)	(5.649)	(0.0745)	(0.973)	(0.676)	(0.131)	(0.139)
Constant	75.55***	0.868***	0.245***	0.528***	0.830***	38.47***	0.208***	1.906**	22.99***	0.590***	0.750***
	(0.757)	(0.0469)	(0.0596)	(0.0692)	(0.0520)	(3.534)	(0.0562)	(0.840)	(0.429)	(0.0798)	(0.0732)
P-value of the joint zero hypothesis	0.448	0.591	0.527	0.362	0.381	0.404	0.257	0.476	0.420	0.120	0.0504
Observations	178	178	178	177	178	178	178	178	116	120	111

Notes: Individually robust standard errors are reported in parentheses. “Age” refers to the age of the participants. “Education” takes 1 for participants with complete compulsory education and 0 otherwise. "Job" takes 1 when they have a job, and 0 otherwise. “Insurance” takes 1 if they have their house insurance, and 0 otherwise. “Own House” takes 1 if they own a house, and 0 otherwise. “House size” refers to the sizes of the house. “Loan Dummy” takes 1 if they pay home loans, and 0 otherwise. “Years of loan” is the duration of their home loans.

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

Table 2: CTB Estimation Allowing for Heterogeneity in Japan (2014 and 2017)

	(1)	(2)	(3)	(4)	(5)	(6)
YEAR		2014			2017	
	β	δ	α	β	δ	α
Without 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)
With 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)
With 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 considering homogeneity	0.0958	0.993	0.772	0.00290	0.721	0.381

Individually clustered standard errors in parentheses. Without Damage is the group indicating subjects whose houses were not damaged. With Minor or Half-damaged House is the group indicating that subjects whose houses suffered minor or half damage. With Almost or Totally-collapsed House is the group indicating subjects whose houses almost or totally collapsed.

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

Table 3: MPL Estimation Allowing for Heterogeneity in Japan (2017)

Deep Parameter	δ	ν	β	$\tilde{\alpha}$	μ
Without House Damage	0.999***	0.0585***	1.015***	0.634***	0.349***
	(0.000276)	(0.0195)	(0.0111)	(0.0773)	(0.0778)
With 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)
With 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 considering homogeneity	0.459	0.0113	0.0632	0.0349	0.727

Notes: Individually clustered standard errors are reported in parentheses. Without Damage is the group indicating subjects whose houses were not damaged. With Minor or Half-damaged House is the group indicating that subjects whose houses suffered minor or half damage. With Almost or Totally-collapsed House is the group indicating subjects whose houses almost or totally collapsed.

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

Table 4: Covariate Balance Test in the Philippines (2014)

VARIABLES	(1) Household Number	(2) Head Sex	(3) Head Age	(4) Head Years of Schooling	(5) Married Dummy	(6) Widow Dummy	(7) Proportion of Foods Cons of Total Cons	(8) Loans in Cash	(9) Business Loans in Cash	(10) Migration Dummy
Satellite Flood Damage	-0.266	0.0490	0.964	-0.700	-0.0125	-0.00500	-0.761	19,918	1,823	0.0285
	(0.445)	(0.0763)	(2.646)	(0.745)	(0.0807)	(0.0669)	(3.153)	(15,601)	(2,223)	(0.0829)
Constant	5.021***	0.833***	57.60***	9.896***	0.813***	0.125**	58.07***	12,532***	1,277	0.191***
	(0.323)	(0.0543)	(1.931)	(0.525)	(0.0569)	(0.0482)	(2.339)	(2,511)	(1,080)	(0.0580)
Observations	97	99	99	99	98	98	92	97	97	97

VARIABLES	(1) Household Number	(2) Head Sex	(3) Head Age	(4) Head Years of Schooling	(5) Married Dummy	(6) Widow Dummy	(7) Proportion of Foods Cons of Total Cons	(8) Loans in Cash	(9) Business Loans in Cash	(10) Migration Dummy
Severity	0.162	-0.0565	0.527	-0.767	0.00664	0.0150	0.251	-4,104	1,169	0.0254
	(0.347)	(0.0604)	(1.944)	(0.628)	(0.0668)	(0.0556)	(2.772)	(9,280)	(1,543)	(0.0689)
Constant	4.706***	0.885***	58.76***	9.195***	0.779***	0.128***	56.98***	19,561**	1,149	0.221***
	(0.239)	(0.0344)	(1.363)	(0.427)	(0.0450)	(0.0362)	(1.829)	(8,848)	(702.3)	(0.0450)
Observations	153	157	157	157	156	156	149	156	156	155

VARIABLES	(1) Household Number	(2) Head Sex	(3) Head Age	(4) Head Years of Schooling	(5) Married Dummy	(6) Widow Dummy	(7) Proportion of Foods Cons of Total Cons	(8) Loans in Cash	(9) Business Loans in Cash	(10) Migration Dummy
Severity with Satellite Flood Damage	0.167	0.117	-1.304	-0.0522	0.102	-0.0890	-0.214	-4,777	2,669	0.124
	(0.469)	(0.0781)	(2.518)	(0.743)	(0.0788)	(0.0621)	(3.469)	(12,717)	(3,104)	(0.0945)
Constant	4.833***	0.821***	58.52***	9.552***	0.773***	0.152***	57.75***	24,326**	1,364	0.167***
	(0.274)	(0.0473)	(1.749)	(0.483)	(0.0521)	(0.0446)	(1.873)	(11,647)	(889.7)	(0.0464)
Observations	97	99	99	99	98	98	92	97	97	97

Notes: Individually robust standard errors are reported in parentheses. “Head Sex” is equal to one when their head is male. “Proportion of Food Cons of Total Cons" is the proportion of food consumption to the total consumption in the month prior Habagat. “Loans in Cash” is the amount of loan in cash before Habagat. “Business Loans in Cash” is the amount of business loan in cash before Habagat. “’Migration Dummy” is equal to one when a household is a migrant. Satellite Flood Damage takes one when households experienced farm damage, as identified by the satellite image. Severity takes 1 when households experienced at least three kinds of damages. Severity with Satellite Flood Damage takes 1 when households experienced at least three kinds of damages, including farm damage, as identified by the satellite image.

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

Table 5: Covariate Balance Test in the Philippines (2018)

VARIABLES	(1) Household Number	(2) Head Sex	(3) Head Age	(4) Head Years of Schooling	(5) Married Dummy	(6) Widow Dummy	(7) Proportion of Foods Cons of Total Cons	(8) Loans in Cash	(9) Business Loans in Cash	(10) Migration Dummy
Satellite Flood Damage	-0.138	0.0127	-1.891	-0.194	-0	0.0400	-0.922	21,620	1,542	0.0215
	(0.450)	(0.0801)	(2.616)	(0.790)	(0.0858)	(0.0690)	(3.449)	(15,937)	(2,410)	(0.0830)
Constant	4.975***	0.850***	59.67***	9.625***	0.800***	0.1000**	57.94***	11,595***	1,622	0.162***
	(0.340)	(0.0571)	(1.944)	(0.596)	(0.0640)	(0.0480)	(2.701)	(2,658)	(1,368)	(0.0613)
Observations	89	91	91	91	90	90	81	86	86	86

VARIABLES	(1) Household Number	(2) Head Sex	(3) Head Age	(4) Head Years of Schooling	(5) Married Dummy	(6) Widow Dummy	(7) Proportion of Foods Cons of Total Cons	(8) Loans in Cash	(9) Business Loans in Cash	(10) Migration Dummy
Severity	0.214	-0.0948	-1.404	0.0335	-0.0381	0.0350	0.711	-6,086	912.7	0.0409
	(0.358)	(0.0653)	(1.976)	(0.657)	(0.0703)	(0.0600)	(2.996)	(11,066)	(1,715)	(0.0720)
Constant	4.620***	0.889***	60.14***	8.819***	0.803***	0.127***	56.07***	21,650**	1,389	0.197***
	(0.256)	(0.0373)	(1.417)	(0.472)	(0.0476)	(0.0398)	(2.028)	(10,650)	(846.7)	(0.0476)
Observations	137	140	140	140	139	139	129	135	135	134

VARIABLES	(1) Household Number	(2) Head Sex	(3) Head Age	(4) Head Years of Schooling	(5) Married Dummy	(6) Widow Dummy	(7) Proportion of Foods Cons of Total Cons	(8) Loans in Cash	(9) Business Loans in Cash	(10) Migration Dummy
Severity with Satellite Flood Damage	0.402	0.0872	-2.391	0.631	0.132	-0.0546	0.704	-8,590	2,396	0.131
	(0.453)	(0.0824)	(2.520)	(0.746)	(0.0809)	(0.0682)	(3.552)	(14,822)	(3,162)	(0.0916)
Constant	4.750***	0.825***	59.51***	9.281***	0.750***	0.143***	57.19***	27,009*	1,636	0.127***
	(0.285)	(0.0509)	(1.780)	(0.544)	(0.0585)	(0.0473)	(2.096)	(13,922)	(1,065)	(0.0455)
Observations	89	91	91	91	90	90	81	86	86	86

Notes: Individually robust standard errors are reported in parentheses. “Head Sex” is equal to one when their head is male. “Proportion of Food Cons of Total Cons" is the proportion of food consumption to the total consumption in the month prior Habagat. “Loans in Cash” is the amount of loan in cash before Habagat. “Business Loans in Cash” is the amount of business loan in cash before Habagat. “’Migration Dummy” is equal to one when a household is a migrant. ’Satellite Flood Damage takes one when households experienced farm damage, as identified by the satellite image. Severity takes 1 when households experienced at least three kinds of damages. Severity with Satellite Flood Damage takes 1 when households experienced at least three kinds of damages, including farm damage, as identified by the satellite image.

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

Table 6: CTB Estimation Allowing for Heterogeneity in the Philippines (2014 and 2018)

	(1)	(2)	(3)	(4)	(5)	(6)
	Satellite Flood Damage		Severity		Severity with Satellite Flood Damage	
YEAR	2014	2018	2014	2018	2014	2018
β_0	0.862***	0.817***	0.864***	0.893***	0.894***	0.903***
	(0.0333)	(0.0274)	(0.0259)	(0.0414)	(0.0333)	(0.0363)
β_1	0.773***	0.784***	0.723***	0.795***	0.833***	0.746***
	(0.0373)	(0.0295)	(0.0433)	(0.0392)	(0.0369)	(0.0560)
δ_0	0.994***	0.995***	0.995***	0.994***	0.994***	0.993***
	(0.00101)	(0.000792)	(0.000837)	(0.000914)	(0.000866)	(0.000844)
δ_1	0.995***	0.994***	0.994***	0.993***	0.993***	0.995***
	(0.000882)	(0.000878)	(0.00115)	(0.00116)	(0.000871)	(0.00141)
α_0	0.109***	0.125***	0.120***	0.121***	0.148***	0.131***
	(0.0136)	(0.0123)	(0.0133)	(0.0137)	(0.0148)	(0.0143)
α_1	0.133***	0.122***	0.123***	0.159***	0.146***	0.157***
	(0.0156)	(0.0126)	(0.0172)	(0.0231)	(0.0150)	(0.0253)
$\beta_0 = \beta_1$	0.0830	0.473	0.0224	0.0808	0.166	0.00550
$\delta_0 = \delta_1$	0.803	0.673	0.221	0.285	0.157	0.807
$\alpha_0 = \alpha_1$	0.154	0.958	0.362	0.258	0.900	0.902
Observations	2352	2184	3792	3384	2352	2184

Individually Clustered Standard errors in parentheses. Subscript "0" and "1" indicate estimated parameters "without damage" and "with damage," respectively. (1) compares the group with farm damage as identified by the satellite image to the group without farm damage. (2) compares the group with number of damages equal to 3 to 6 to the group with number of damages equal to 0 to 2; (3) compares the same strategy as (2) but uses the satellite-identified farm damage instead of the self-reported farm damage.

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

Table 7: MPL Estimation Considering Heterogeneity in the Philippines (2014)

Deep Parameter	δ	ν	β	$\tilde{\alpha}$	μ
Satellite Flood Damage=0	0.996***	0.128**	0.955***	0.633***	0.174**
	(0.00144)	(0.0516)	(0.0252)	(0.140)	(0.0679)
Satellite Flood Damage=1	0.993***	0.272***	0.860***	0.221	0.303***
	(0.00201)	(0.0808)	(0.0595)	(0.179)	(0.0771)
Observations			14112		
P-value of the null hypothesis considering homogeneity	0.216	0.132	0.140	0.0706	0.210

Deep Parameter	δ	ν	β	$\tilde{\alpha}$	μ
Severity=0	0.995***	0.184***	0.918***	0.493***	0.258***
	(0.00139)	(0.0555)	(0.0289)	(0.139)	(0.0702)
Severity=1	0.992***	0.339***	0.827***	0.120	0.341***
	(0.00171)	(0.0795)	(0.0577)	(0.157)	(0.0683)
Observations			22752		
P-value of the null hypothesis considering homogeneity	0.106	0.110	0.160	0.0747	0.395

Deep Parameter	δ	ν	β	$\tilde{\alpha}$	μ
Severity with Satellite Flood Damage=0	0.996***	0.150***	0.960***	0.554***	0.208***
	(0.00133)	(0.0475)	(0.0245)	(0.130)	(0.0641)
Severity with Satellite Flood Damage=1	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 considering homogeneity	0.250	0.177	0.0209	0.156	0.382

Notes: Individually clustered standard errors are reported in parentheses. Satellite Flood Damage takes one if households experienced farm damage, as identified by the satellite image. Severity takes 1 when households experienced at least three kinds of damages. Severity with Satellite Flood Damage takes 1 when households experienced at least three kinds of damages, including farm damage, as identified by the satellite image.

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

Table 8: MPL Estimation Considering Heterogeneity in the Philippines (2018)

Deep Parameter	δ	ν	β	$\tilde{\alpha}$	μ
Satellite Flood Damage=0	0.998***	0.0663**	0.935***	0.713***	0.0974***
	(0.000857)	(0.0310)	(0.0294)	(0.126)	(0.0378)
Satellite Flood Damage=1	0.998***	0.133***	0.863***	0.479***	0.255***
	(0.000844)	(0.0482)	(0.0522)	(0.175)	(0.0867)
Observations			13104		
P-value of the null hypothesis considering homogeneity	0.622	0.244	0.231	0.278	0.0957

Deep Parameter	δ	ν	β	$\tilde{\alpha}$	μ
Severity=0	0.998***	0.112**	0.950***	0.587***	0.230***
	(0.000868)	(0.0466)	(0.0223)	(0.158)	(0.0839)
Severity=1	0.997***	0.129***	0.871***	0.493***	0.199***
	(0.000801)	(0.0332)	(0.0363)	(0.115)	(0.0466)
Observations			20304		
P-value of the null hypothesis considering homogeneity	0.618	0.774	0.0624	0.634	0.747

Deep Parameter	δ	ν	β	$\tilde{\alpha}$	μ
Severity with Satellite Flood Damage=0	0.998***	0.0920***	0.945***	0.632***	0.162***
	(0.000818)	(0.0355)	(0.0226)	(0.131)	(0.0576)
Severity with Satellite Flood Damage=1	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 considering homogeneity	0.742	0.892	0.0978	0.714	0.729

Notes: Individually clustered standard errors are reported in parentheses. Satellite Flood Damage takes one if households experienced farm damage, as identified by the satellite image. Severity takes 1 if households experienced at least three kinds of damages. Severity with Satellite Flood Damage takes 1 if households experienced at least three kinds of damages, including farm damage, as identified by the satellite image.

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

Table 9: Emotional Change in Japan (2014 and 2017)

Participants in 2014			
VARIABLES	Desperate Feeling	Hopeless Life	Something Bad
With Minor or Half Damaged House	0.0634	0.0974**	0.0138
	(0.0813)	(0.0459)	(0.0605)
With Almost or Totally Collapsed House	0.288***	0.194**	0.0615
	(0.104)	(0.0756)	(0.0814)
Constant	0.277***	0.0426	0.128**
	(0.0658)	(0.0297)	(0.0491)
Observations	186	185	183

Participants in 2017			
VARIABLES	Desperate Feeling	Hopeless Life	Something Bad
With Minor or Half Damaged House	0.0919	0.102**	-0.00266
	(0.0787)	(0.0460)	(0.0596)
With Almost or Totally Collapsed House	0.319***	0.142**	0.0301
	(0.0998)	(0.0674)	(0.0770)
Constant	0.245***	0.0377	0.132***
	(0.0596)	(0.0264)	(0.0469)
Observations	178	178	175

Notes: Individually clustered 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. Without Damage takes 1 if subjects' houses were not damaged. With Minor or Half-damaged House takes 1 if subjects' houses suffered minor or half damage. With Almost or Totally-collapsed House takes 1 if subjects' houses almost or totally collapsed.

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

Table 10: Emotional Change in the Philippines (2018)

VARIABLES	$\mathbb{1}$(Subjective Life Expectancy Declined)					
	(1)	(2)	(3)	(4)	(5)	(6)
Satellite Flood Damage	0.0530	0.0577				
	(0.0473)	(0.0528)				
Severity			0.0481	0.0724*		
			(0.0432)	(0.0435)		
Severity with Satellite Flood Damage					0.103*	0.120*
					(0.0604)	(0.0622)
Constant	0.0270	1.710*	0.0429*	1.467*	0.0185	1.983**
	(0.0270)	(0.866)	(0.0244)	(0.811)	(0.0186)	(0.895)
Observations	87	87	136	136	87	87
Control Variables	No	Yes	No	Yes	No	Yes

Notes: Individually clustered standard errors are reported in parentheses. $\mathbb{1}$(Subjective Life Expectancy Declined) takes one if subjects perceive a decline in their longevity after "Habagat." Satellite Flood Damage takes one if households experience farm damage, as identified by the satellite image. Severity takes 1 if households experienced at least three kinds of damages. Severity with Satellite Flood Damage takes 1 if households experienced at least three kinds of damages, including farm damage, as identified by the satellite image. Control Variables include female dummy, log of their age, years of education, and their expected life expectancy.

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

Table 11: CTB Estimation Considering Heterogeneity and Liquidity Constraints in the Philippines (2014)

Deep Parameter	β	δ	α	τ_0	τ_1
Satellite Flood Damage=0	0.774***	0.993***	0.127***	0.145***	-1.03e-07***
	(0.0452)	(0.000966)	(0.0151)		
Satellite Flood Damage=1	0.647***	0.993***	0.195***	(0.0342)	(3.64e-08)
	(0.0646)	(0.00145)	(0.0324)		
Observations			2352		
P-value of the null hypothesis	0.0849	0.673	0.0633		
Deep Parameter	β	δ	α	τ_0	τ_1
Severity=0	0.677***	0.994***	0.176***	0.173***	-1.19e-07**
	(0.0497)	(0.00107)	(0.0218)		
Severity=1	0.627***	0.993***	0.174***	(0.0322)	(4.76e-08)
	(0.0550)	(0.00105)	(0.0209)		
Observations			3768		
P-value of the null hypothesis	0.475	0.667	0.955		
Deep Parameter	β	δ	α	τ_0	τ_1
Severity with Satellite Flood Damage=0	0.774***	0.993***	0.142***	0.146***	-1.17e-07***
	(0.0421)	(0.000934)	(0.0169)		
Severity with Satellite Flood Damage=1	0.579***	0.995***	0.195***	(0.0349)	(3.97e-08)
	(0.0782)	(0.00177)	(0.0347)		
Observations			2352		
P-value of the null hypothesis	0.0225	0.297	0.175		

Notes: Individually clustered standard errors are reported in parentheses. Satellite Flood Damage takes one if households experienced farm damage, as identified by the satellite image. Severity takes 1 if households experienced at least three kinds of damages. Severity with Satellite Flood Damage takes 1 if households experienced at least three kinds of damages, including farm damage, as identified by the satellite image.

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

Table 12: CTB Estimation Considering Heterogeneity and Liquidity Constraints in the Philippines (2018)

Deep Parameter	β	δ	α	τ_0	τ_1
Satellite Flood Damage=0	0.787***	0.994***	0.126***	0.194***	-2.41e-08
	(0.0529)	(0.00121)	(0.0193)		
Satellite Flood Damage=1	0.661***	0.995***	0.149***	(0.0524)	(8.68e-08)
	(0.0585)	(0.00101)	(0.0195)		
Observations			2184		
P-value of the null hypothesis	0.0737	0.297	0.400		

Deep Parameter	β	δ	α	τ_0	τ_1
Severity=0	0.763***	0.996***	0.145***	0.178***	6.98e-09
	(0.0522)	(0.000936)	(0.0165)		
Severity=1	0.703***	0.994***	0.140***	(0.0391)	(7.10e-08)
	(0.0464)	(0.00103)	(0.0173)		
Observations			3384		
P-value of the null hypothesis	0.317	0.151	0.846		

Deep Parameter	β	δ	α	τ_0	τ_1
Severity with Satellite Flood Damage=0	0.785***	0.995***	0.136***	0.194***	-4.63e-08
	(0.0514)	(0.000963)	(0.0172)		
Severity with Satellite Flood Damage=1	0.633***	0.994***	0.138***	(0.0481)	(8.57e-08)
	(0.0613)	(0.00132)	(0.0220)		
Observations			2184		
P-value of the null hypothesis	0.0388	0.797	0.955		

Notes: Individually clustered standard errors are reported in parentheses. Satellite Flood Damage takes one if households experienced farm damage, as identified by the satellite image. Severity takes 1 if households experienced at least three kinds of damages. Severity with Satellite Flood Damage takes 1 if households experienced at least three kinds of damages, including farm damage, as identified by the satellite image.

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

Table 13: CTB Estimation Allowing for Heterogeneity and Sample Selection in Japan (2014 and 2017)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
YEAR	2014				2017			
	β	δ	α	Covariance	β	δ	α	Covariance
Without House Damage	0.999***	0.994***	0.289***		0.991***	0.994***	0.194***	
	(0.0342)	(0.00124)	(0.0352)		(0.0214)	(0.000810)	(0.0151)	
With Minor or Half-damaged House	0.965***	0.994***	0.271***	-0.724***	0.919***	0.994***	0.225***	-0.954***
	(0.0221)	(0.000845)	(0.0215)	(0.0808)	(0.0313)	(0.000856)	(0.0168)	(0.0943)
With Almost or Totally-collapsed House	0.880***	0.995***	0.256***		0.835***	0.994***	0.198***	
	(0.0446)	(0.00109)	(0.0298)		(0.0416)	(0.000808)	(0.0176)	
Observations	154,114				154,107			
P-value of the null hypothesis:								
Without House Damage = With Minor/Half-damaged	0.409	0.701	0.656		0.0616	0.895	0.166	
Without House Damage = With Almost/Totally-collapsed	0.0370	0.612	0.471		0.0008	0.925	0.877	
With Minor/Half-damaged = With Almost/Totally-collapsed	0.0962	0.829	0.686		0.107	0.976	0.251	
All of the three are the same	0.110	0.879	0.771		0.0021	0.990	0.337	

Individually clustered standard errors in parentheses. Without Damage is the group indicating subjects whose houses were not damaged. With Minor or Half-damaged House is the group indicating that subjects whose houses suffered minor or half damage. With Almost or Totally-collapsed House is the group indicating subjects whose houses almost or totally collapsed. We employ age, age-squared, job dummy and education dummy as covariates in the first-stage sample selection equation which is jointly estimated with the second-stage equation shown in this table by the maximum likelihood method. "'Covariance' indicates the estimated covariance of the error terms in the first- and second-stages.

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

A Appendix: For Online Publication Only

A.1 Two Experiments: The Multiple Price List (MPL) Experiment and The Holt and Laury (2002) Experiment

A.1.1 The Multiple Price List (MPL) Experiment

In the Multiple Price List (MPL) experiment, we set the same interest rates, experimental budgets, and delay lengths as the ones in the CTB experiments. Also, subjects were required to respond to all the tasks where future payments were guaranteed by the University of Tokyo for the subjects in Iwanuma city and by a local head investigator for the subjects in the East Laguna Village if a future payment was chosen for experimental payout.

We employ the binary choices of the subjects to estimate the parameters (β, δ) with an error structure that recognizes the panel nature of the data. When subjects choose sooner payment that is paid out at time t provides the discounted utility $u(X)$ when $t = 0$ or $\beta\delta^t u(X)$ when $t \neq 0$. On the other hand, the discounted utility of later payments is $\beta\delta^k u(X)$ when $t = 0$ or $\beta\delta^{t+k}u(X)$ when $t \neq 0$. Especially, assuming the time separable CRRA utility function (as given in Equations (6) and (7)) and $\tilde{\alpha} = 0$, we can rewrite these discounted values as follows:

$$PV_X = \begin{cases} X & if\ t = 0 \\ \beta\delta^t X & if\ t \neq 0 \end{cases} \tag{16}$$

$$PV_Y = \begin{cases} \beta\delta^k Y & if\ t = 0 \\ \beta\delta^{t+k} Y & if\ t \neq 0. \end{cases} \tag{17}$$

An index of the difference between these discounted values can be defined as

$$\nabla PV = \frac{PV_Y^{\frac{1}{\nu}}}{PV_X^{\frac{1}{\nu}} + PV_Y^{\frac{1}{\nu}}}, \tag{18}$$

where ν is a structural noise parameter to allow some errors for the discount rate choices. As $\nu \to 0$, this specification indicates that choices are determined with no errors. On the other hand, as ν becomes large, this specification converges to a situation where choices are totally random.

The likelihood of the discount rate responses, conditional on the specification of the time separable utility function depends on the parameters β, δ and ν. Therefore, we estimate the following conditional log-likelihood function:

$$lnL^{DR}(\beta, \delta; X, Y) = \sum_i (ln(\nabla PV | C_{Di} = 1) + ln(1 - \nabla PV | C_{Di} = 0)), \tag{19}$$

where C_i takes 1 when later payment is chosen and take 0 when sooner payment is chosen.

A.1.2 The Holt and Laury (2002) Experiment

The Holt and Laury (2002) experiment is one of the most popular experiments using a multiple price list (MPL) design to elicit an individual's attitude toward risks. In this 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. There are two options, A and B. Table 2 and 3 illustrate the basic payoff matrix presented to subjects in Japan and the Philippines, respectively. For example, in these two tables, the first row shows that lottery A offered a 10% chance of receiving 5000 Japanese Yen (JPY) in Japan (around 50USD) or 200 Philippine Peso (PHP) in the Philippines (around 4 USD), and a 90% chance of receiving 4000 JPY or 160 PHP. On the other hand, lottery B offered a 10 % chance of receiving 9625 JPY in Japan or 385 PHP in the Philippines, and a 90% chance of receiving 250 JPY in Japan or 10 PHP in the Philippines. As one proceeds down the matrix, the expected value of lottery B increases more compared to that of lottery A does so that subjects are more likely to choose lottery B. We asked the subject to separately choose A or B in each row. The last row basically tells whether each subject understands the Holt and Laury (2002) experiment or not.

We can write out a likelihood function for the risky choices to estimate the risk preference parameter, $\tilde{\alpha}$. For each outcome of each lottery A and B, the probabilities $p(M_{ij})$ is assigned by the experimenter. Then, since there are only two outcomes in lottery A and B, the expected utility for lottery i (i = A or B) becomes:

$$EU_i = \sum_{j=1,2} (p(M_j) \times u(M_j)). \tag{20}$$

For example, when subjects choose Lottery A, $M_1 = 5000$ JPY, $M_2 = 4000$ JPY in Japan or $M_1 = 200$ PHP, $M_2 = 160$ PHP in the Philippines, $p(M_1)$ ranges from 0.1 to 1 and $p(M_2)$ ranges from 0 to 0.9. On the other hand, when subjects choose Lottery B, $M_1 = 9625$ JPY, $M_2 = 250$ JPY in Japan or $M_1 = 385$ PHP, $M_2 = 10$ PHP in the Philippines, $p(M_1)$ ranges from 0.1 to 1 and $p(M_2)$ ranges from 0 to 0.9. A simple stochastic specification from Holt and Laury (2002) is employed to formulate likelihoods conditional on the model. The ratio of the two expected utilities from lottery A and B is expressed as follows:.

$$\nabla EU = \frac{EU_B^{\frac{1}{\mu}}}{EU_A^{\frac{1}{\mu}} + EU_B^{\frac{1}{\mu}}}, \tag{21}$$

where EU_A refers to the expected utility for Lottery A, EU_B refers to expected utility for Lottery B and μ is a structural noise parameter for the risk aversion choices, just as ν is a noise parameter for the discount rate choices. As $\mu \to 0$, this specification collapses to the deterministic choice model, but as μ becomes larger and larger, the choices become completely random. This ratio is linked to the observed choices by specifying that the Lottery B is chosen when $\nabla EU > \frac{1}{2}$.

In this framework, we can write out the likelihood function which is dependent on the parameters α and μ as well as the choices that subjects made. Then the conditional log-likelihood function to estimate parameters, α and μ, is as follows:

$$lnL^{RA}(\tilde{\alpha}, \mu; A, B) = \sum_i (ln(\nabla EU | C_{Ri} = 1) + ln(1 - \nabla EU | C_{Ri} = 0)), \qquad (22)$$

where C_{Ri} takes 1 when Lottery B is chosen and take 0 when Lottery A is chosen.

A.2 Graphical Representations of Individual Choices in Japan

Table 1 shows the choice sets of CTB experiments used both in Japan and the Philippines for all the experimental waves. In Figure 1 and 2, respectively for 2014 and 2017, we compare graphically the results of choices under $\{t = 0, k = 35\}$ or $\{t = 0, k = 63\}$ with the future choices under $\{t = 35, k = 35\}$ or $\{t = 63, k = 63\}$. These figures show consistency of choices in short-run (2014) and long-run (2017). The observed decision patterns with the MPL method shows a similar pattern (Figure 3).

We also show the results of Holt and Laury (2002) experiment based on Tables 2 and 3 graphically. Figure 4 demonstrates that as the probability of winning the larger prize increases, subjects decrease the probability of choosing the safer lottery, i.e., Lottery A. Furthermore, when the probability of winning the larger prize becomes sufficiently low, most subjects choose the safer lottery, indicating the existence of risk aversion, highlighting the importance of the curvature parameters of utility function.

We also allow heterogenous impacts of the disaster on individual preferences. The results summarized by degree of home damages indicate that damages make people more present-biased: In Figure 5 and 6, we can compare the case $\{t = 0, k = 35\}$ or $\{t = 0, k = 63\}$ with the one where $\{t = 35, k = 35\}$ or $\{t = 63, k = 63\}$ based on the 2014 CTB experiments. 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 related. In the 2017 CTB experiments, we obtain somewhat similar results (Figure 7 and 8). Based on the MPL method, the nexus between disaster damage and presentbiasness becomes more slient (Figure 9 and 10 for 2017).

As for the disaster impact on risk attitudes, we present Holt and Laury (2002) experiment results allowing heterogeneity across degree of damages. Intriguingly, individuals with more house damages show less risk aversion (Figure 11). Those who suffered house damage choose the safer lottery less even when the probability of winning larger prize is close to zero. For example, when the probability of winning the larger prize is 0.1, while more than 90 % of individuals without any house damage choose the safer lottery, less than 80 % of individuals with some house damages select the safer lottery.

A.3 Graphical Representations of Individual Choices in the Philippines

The results of overall CTB and MPL experiments are reported, respectively, in Figure 12 and Figure 13 for the 2014 experiments. In both CTB and MPL experiments, higher proportion of subjects select sooner payment under the setting of $\{t = 0, k = 35\}$ than the situation where $\{t = 35, k = 35\}$, indicating overall present biasness in the Philippines.

Using the results of Holt and Laury (2002) experiments, we also show the overall patter of risk aversion in the Philippines. Figure 14 clearly indicates that the probability of winning the larger prize and the probability of choosing the safer lottery is negatively correlated. Also, this relationship is concave, suggesting that the subjects are overall risk averse.

We also examine the impact of the floods on individual preference graphically. According to the 2014 CTB experiment results shown in Figure 15-20 and the 2014 MPL experiment results in Figure 21-26, generally higher proportion of subjects select sooner payment under the setting of $\{t = 0, k = 35\}$ than the situation where $\{t = 35, k = 35\}$. These results indicate that disaster damages make people more presentbias.

As for the risk attitude elicited by the Holt and Laury (2002) experiments in 2014, Figure 27-29 show that disaster damages make people less risk averse.

The results obtained from the CTB and MPL as well as the Holt and Laury (2002) experiments conducted in 2018 also show the same qualitative results (Figure 30-47).

We find that disaster exposure makes individuals more present-biased and less risk-averse, and that the impact lasted for 6 years in the Philippines. We obtain qualitatively the same results as the ones in Japan regardless of distinctive differences in socio-economic conditions (i.e., systematically lower income and education level in the Philippines) and disaster types (earthquake and tsunami in Japan and floods in the Philippines). Our findings suggest that the existing mixed empirical evidence can be attributed to the lack of an integrated and consistent framework as well as accurate data on disaster damages, rather than variations in literacy or education levels of experimental subjects.

A.4 Pooled Data Analysis

To exploit the dynamic nature of two experiments in Japan and in the Philippines, we employ the following strategy: we pool two rounds of experiment in each area, create repeated cross-section datasets, and estimate each year's parameters jointly and check whether each disaster has persistent impacts on individual preferences. Table 6 - 9 shows the estimation results using the two rounds of CTB in both places. We find that the impacts of the two disasters persistent over the six years. Accordingly, we believe we can conclude that both disasters generated long-lasting impacts on individual hyperbolic discounting and risk aversion parameters.

A.5 Possible Mechanisms

In empirical analyses, we find that being hit by the Great East Japan Earthquake or the floods makes individual significantly more present-biased and less risk averse than those who are unaffected. In this section, we explain why disasters make people more present-biased using the theoretical arguments based on Chakraborty et al. (2019).

We consider consumption streams in discrete time (i.e. $T = \mathbb{N}$). In this case, intertemporal behavior is usually characterized by properties of the discount-function, and under time invariance it depends only on the distance between the evaluation time and consumption time. Let $D(\cdot)$ be the decision maker (DM)'s discount-function, so the utility of consuming x after τ periods is $D(\tau)u(x)$, where u is a real value function on X. The DM's (one-period) impatience at t is $D(t)/D(t+1)$ and (k-period) impatience at t is $D(t)/D(t+k)$. We specify the intertemporal utility function based on **?**. In the model, every consumption path $\mathbf{c} = (c_0, c_1, c_2, \cdots)$ is subject to a mix of a survival rate of a disaster, p, and a constant hazard rate of termination except for a disaster, $r \in (0,1)$. The utility is evaluated using Rank Dependent Utility with probability weighting function $g(\cdot)$. Then, the utility of the consumption stream is

$$U(\mathbf{c}, r) = \sum_{t=0}^{\infty} g(p^{\mathbb{1}(t>0)}(1-r)^t)\delta^t u(c_t) \tag{23}$$

where δ is a constant pure time preference parameter, $g : [0,1] \to [0,1]$ is a strictly increasing function, and $u(\cdot)$ is the DM's felicity function. Given this representation, the composite discount function at period t is

$$D(t) = \delta^t g(p^{\mathbb{1}(t>0)}(1-r)^t) \tag{24}$$

We connect this to the empirical findings in Japan and the Philippines. We assume that households have the prior belief of $p_0^{\mathbb{1}(t>0)}(1-r)^t$ before a disaster and the posterior belief of $p_1^{\mathbb{1}(t>0)}(1-r)^t$ after a disaster, where $p_0 > p_1$. Moreover, we also assume that households consider the normal hazard rate and the survival rate of a disaster separately for a weighting function, i.e., $g(p^{\mathbb{1}(t>0)}(1-r)^t) = f(p^{\mathbb{1}(t>0)})h((1-r)^t)$. Then, we can show the following theorem which implies that belief updating makes people's discounting be more hyperbolic.

Theorem 1. *Suppose the intertemporal utility function is $U(\mathbf{c},r) = \sum_{t=0}^{\infty} g(p^{\mathbb{1}(t>0)}(1-r)^t)\delta^t u(c_t)$ where $g(p^{\mathbb{1}(t>0)}(1-r)^t) = f(p^{\mathbb{1}(t>0)})h((1-r)^t)$. Then, after a disaster, he/she shows (one-period) impatience more at the current period and the same level of impatience at other periods.*

Proof of Theorem 1. *The DM's discount function before a disaster is denoted by $D(\cdot)$ and the DM's discount function after a disaster is denoted by $\tilde{D}(\cdot)$. Then, since the prior belief before a disaster is $p_0^{\mathbb{1}(t>0)}(1-r)^t$ and the posterior belief after a disaster is $p_1^{\mathbb{1}(t>0)}(1-r)^t$, the relationship between the one-period impatiences at $t=0$ before and after a disaster is as follows.*

$$\frac{\tilde{D}(0)}{\tilde{D}(1)} = \frac{g(0)}{\delta g(p(1-r))} = \frac{f(1)h(0)}{\delta f(p)h((1-r))} > \frac{h(0)}{\delta h((1-r))} = \frac{D(0)}{D(1)} \tag{25}$$

On the other hand, the relationship between the one-period impatiences at $t \neq 0$ before and after a disaster is as follows.

$$\frac{\tilde{D}(t)}{\tilde{D}(t+1)} = \frac{g(p_1(1-r)^t)}{\delta g(p_1(1-r)^{t+1})} = \frac{f(p_1)h((1-r)^t)}{\delta f(p_1)h((1-r)^{t+1}))} = \frac{f(p_0)h((1-r)^t)}{\delta f(p_0)h((1-r)^{t+1})} = \frac{D(t)}{D(t+1)} \tag{26}$$

Q.E.D.

Table 1: Intertemporal Experimental Parameters in CTB for Japan and the Philippines

Choice Set	t (days until first payment)	k (delay)	P (price ratios): $Px_t + x_{t+k} = Y$
CTB_1	0	35	1.05, 1.11, 1.18, 1.25, 1.43, 1.82
CTB_2	0	63	1.00, 1.05, 1.18, 1.33, 1.67, 2.22
CTB_3	35	35	1.05, 1.11, 1.18, 1.25, 1.43, 1.82
CTB_4	35	63	1.00, 1.05, 1.18, 1.33, 1.67, 2.22

Notes: The price ratios for k=35 correspond to yearly interest rates of 65%, 164%, 312%, 529%, 1301% and 4276%. The price ratios for k=35 correspond to yearly interest rates of 0%, 33%, 133%, 304%, 823% and 2093%. $Y = 10000$ JPY in Japan and $Y = 400$ PHP in the Philippines.

Table 2: Payoff Matrix in Lottery Choice Experiments in 2017 in Japan

Lottery A				Lottery B				
p	JPY	p	JPY	p	JPY	p	JPY	Open CRRA Interval if Subject Switches
0.1	5000	0.9	4000	0.1	9625	0.9	250	$(-\infty, -1.71)$
0.3	5000	0.7	4000	0.3	9625	0.7	250	$(-0.95, -0.49)$
0.5	5000	0.5	4000	0.5	9625	0.5	250	$(-0.15, 0.14)$
0.7	5000	0.3	4000	0.7	9625	0.3	250	$(0.41, 0.68)$
0.9	5000	0.1	4000	0.9	9625	0.1	250	$(0.97, 1.37)$
1	5000	0	4000	1	9625	0	250	$(1.37, \infty)$

Notes: All columns except the last column were shown to subjects.

Table 3: Payoff Matrix in Lottery Choice Experiments in 2014 and 2018 in the Philippines

Lottery A				Lottery B				
p	PHP	p	PHP	p	PHP	p	PHP	Open CRRA Interval if Subject Switches
0.1	200	0.9	160	0.1	385	0.9	10	$(-\infty, -1.71)$
0.3	200	0.7	160	0.3	385	0.7	10	$(-0.95, -0.49)$
0.5	200	0.5	160	0.5	385	0.5	10	$(-0.15, 0.14)$
0.7	200	0.3	160	0.7	385	0.3	10	$(0.41, 0.68)$
0.9	200	0.1	160	0.9	385	0.1	10	$(0.97, 1.37)$
1	200	0	160	1	385	0	10	$(1.37, \infty)$

Notes: All columns except the last column were shown to subjects.

Table 4: CTB Estimation Allowing for Homogeneity in Japan (2014 and 2017)

	Participants in 2014			Participants in 2017		
	(1)	(2)	(3)	(4)	(5)	(6)
Method	NLS	NLS	OLS	NLS	NLS	OLS
β	0.998***	0.998***	1.010***	0.983***	0.983***	0.979***
	(0.00685)	(0.00721)	(0.0179)	(0.00478)	(0.00641)	(0.0187)
δ	0.999***	0.999***	1.002***	0.999***	0.999***	1.001***
	(9.98e-05)	(0.000179)	(0.000577)	(6.77e-05)	(0.000123)	(0.000466)
α	0.144***	0.144***	0.247***	0.082***	0.082***	0.189***
	(0.00517)	(0.0112)	(0.0130)	(0.00293)	(0.00604)	(0.00805)
Observations	4,464	4,464	4,464	4,296	4,296	4,296
Cluster	NO	YES	YES	NO	YES	YES

Notes: Individually clustered standard errors are reported in parentheses in column (2) and (3).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: CTB Estimation Allowing for Homogeneity in the Philippines (2014 and 2018)

	Participants in 2014			Participants in 2018		
	(1)	(2)	(3)	(4)	(5)	(6)
Method	NLS	NLS	OLS	NLS	NLS	OLS
β	0.844***	0.844***	0.802***	0.893***	0.893***	0.864***
	(0.0142)	(0.0170)	(0.0223)	(0.0139)	(0.0188)	(0.0225)
δ	0.995***	0.995***	0.994***	0.996***	0.996***	0.995***
	(0.000225)	(0.000505)	(0.000620)	(0.000216)	(0.000487)	(0.000578)
α	0.282***	0.282***	0.147***	0.241***	0.241***	0.124***
	(0.0122)	(0.0182)	(0.0106)	(0.0110)	(0.0173)	(0.00880)
Observations	3,792	3,792	3,792	3,384	3,384	3,384
Cluster	NO	YES	YES	NO	YES	YES

Notes: Individually clustered standard errors are reported in parentheses in column (2) and (3).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Pooled CTB Estimation Considering Time Heterogeneity in Japan

Deep Parameters	β			δ			α		
	(1) Without	(2) Minor or Half	(3) Almost or Totally	(4) Without	(5) Minor or Half	(6) Almost or Totally	(7) Without	(8) Minor or Half	(9) Almost or Totally
YEAR=2014	1.057***	1.022***	0.937***	1.001***	1.002***	1.001***	0.262***	0.247***	0.234***
	(0.0366)	(0.0226)	(0.0431)	(0.00121)	(0.000765)	(0.00126)	(0.0289)	(0.0178)	(0.0247)
YEAR=2017	1.045***	0.980***	0.893***	1.001***	1.002***	1.000***	0.177***	0.202***	0.181***
	(0.0219)	(0.0304)	(0.0401)	(0.000737)	(0.000888)	(0.000869)	(0.0125)	(0.0136)	(0.0145)
P-value of the null hypothesis that the dif b/w (1)-(2) in 2014 is equal to the dif b/w (1)-(2) in 2017									0.60
P-value of the null hypothesis that the dif b/w (1)-(3) in 2014 is equal to the dif b/w (1)-(3) in 2017									0.66
P-value of the null hypothesis that the dif b/w (2)-(3) in 2014 is equal to the dif b/w (2)-(3) in 2017									0.98
P-value of the null hypothesis that the dif b/w (4)-(5) in 2014 is equal to the dif b/w (4)-(5) in 2017									0.63
P-value of the null hypothesis that the dif b/w (4)-(6) in 2014 is equal to the dif b/w (4)-(6) in 2017									0.94
P-value of the null hypothesis that the dif b/w (5)-(6) in 2014 is equal to the dif b/w (5)-(6) in 2017									0.60
P-value of the null hypothesis that the dif b/w (7)-(8) in 2014 is equal to the dif b/w (7)-(8) in 2017									0.31
P-value of the null hypothesis that the dif b/w (7)-(9) in 2014 is equal to the dif b/w (7)-(9) in 2017									0.47
P-value of the null hypothesis that the dif b/w (8)-(9) in 2014 is equal to the dif b/w (8)-(9) in 2017									0.81

Notes: Individually clustered standard errors are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Pooled CTB Estimation Considering Time Heterogeneity in the Philippines (Satellite Flood Damage)

Deep Parameters	β		δ		α	
	(1)	(2)	(3)	(4)	(5)	(6)
Satellite Flood Damage	NO	YES	NO	YES	NO	YES
YEAR=2014	0.862***	0.773***	0.994***	0.993***	0.121***	0.159***
	(0.0332)	(0.0391)	(0.000912)	(0.00115)	(0.0136)	(0.0230)
YEAR=2018	0.893***	0.795***	0.994***	0.995***	0.109***	0.133***
	(0.0408)	(0.0365)	(0.000986)	(0.000892)	(0.0123)	(0.0154)
P-value of the null hypothesis that the dif b/w (1)-(2) in 2014 is equal to that in 2018						0.912
P-value of the null hypothesis that the dif b/w (3)-(4) in 2014 is equal to that in 2018						0.363
P-value of the null hypothesis that the dif b/w (5)-(6) in 2014 is equal to that in 2018						0.656

Notes: Individually clustered standard errors are reported in parentheses. Satellite Flood Damage is identified by the satellite image.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Pooled CTB Estimation Considering Time Heterogeneity in the Philippines (Severity)

Deep Parameters	β		δ		α	
	(1)	(2)	(3)	(4)	(5)	(6)
Severity	NO	YES	NO	YES	NO	YES
YEAR=2014	0.817***	0.784***	0.994***	0.993***	0.148***	0.146***
	(0.0274)	(0.0368)	(0.000865)	(0.000870)	(0.0147)	(0.0150)
YEAR=2018	0.894***	0.833***	0.995***	0.994***	0.125***	0.122***
	(0.0331)	(0.0289)	(0.000788)	(0.000870)	(0.0119)	(0.0120)
P-value of the null hypothesis that the dif b/w (1)-(2) in 2014 is equal to that in 2018						0.652
P-value of the null hypothesis that the dif b/w (3)-(4) in 2014 is equal to that in 2018						0.497
P-value of the null hypothesis that the dif b/w (5)-(6) in 2014 is equal to that in 2018						0.968

Notes: Individually clustered standard errors are reported in parentheses. Severity is based on whether households experienced at least 3 kinds of damages.

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

Table 9: Pooled CTB Estimation Considering Time Heterogeneity in the Philippines (Severity with Satellite Flood Damage)

Deep Parameters	β		δ		α	
	(1)	(2)	(3)	(4)	(5)	(6)
Severity with Satellite Flood Damage	NO	YES	NO	YES	NO	YES
YEAR=2014	0.864***	0.723***	0.993***	0.995***	0.131***	0.157***
	(0.0259)	(0.0558)	(0.000842)	(0.00141)	(0.0143)	(0.0252)
YEAR=2018	0.903***	0.746***	0.995***	0.994***	0.120***	0.123***
	(0.0358)	(0.0422)	(0.000834)	(0.00113)	(0.0123)	(0.0165)
P-value of the null hypothesis that the dif b/w (1)-(2) in 2014 is equal to that in 2018						0.846
P-value of the null hypothesis that the dif b/w (3)-(4) in 2014 is equal to that in 2018						0.275
P-value of the null hypothesis that the dif b/w (5)-(6) in 2014 is equal to that in 2018						0.504

Notes: Individually clustered standard errors are reported in parentheses. Severity with Satellite Flood Damage is based on whether households experienced at least 3 kinds of damages including farm damage identified by the satellite image.

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

Table 10: MPL Estimation Allowing for Homogeneity in Japan

Deep Parameter	δ	ν	β
	0.998***	0.196***	0.989***
	(0.000322)	(0.0196)	(0.0197)

Notes: Individually clustered standard errors are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Holt and Laury Estimation Allowing for Homogeneity in Japan

Deep Parameter	α	μ
	0.443***	0.359***
	(0.0457)	(0.0342)

Notes: Individually clustered standard errors are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: MPL Estimation Allowing for Homogeneity in Japan (2017)

Deep Parameter	δ	ν	β	$\tilde{\alpha}$	μ
	0.999***	0.109***	0.994***	0.443***	0.359***
	(0.000201)	(0.0150)	(0.0110)	(0.0457)	(0.0342)

Notes: Individually clustered standard errors are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: MPL Estimation Allowing for Homogeneity in the Philippines (2014)

Deep Parameter	δ	ν	β
	0.991***	0.372****	0.828***
	(0.000834)	(0.0317)	(0.0340)

Notes: Individually clustered standard errors are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Holt and Laury Estimation Allowing for Homogeneity in the Philippines (2014)

Deep Parameter	α	μ
	0.320***	0.308***
	(0.0604)	(0.0261)

Notes: Individually clustered standard errors are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: MPL Estimation Allowing for Homogeneity in the Philippines (2018)

Deep Parameter	δ	ν	β
	0.994***	0.266***	0.822***
	(0.000555)	(0.0215)	(0.0293)

Notes: Individually clustered standard errors are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Holt and Laury Estimation Allowing for Homogeneity in the Philippines (2018)

Deep Parameter	α	μ
	0.532***	0.221***
	(0.0999)	(0.0468)

Notes: Individually clustered standard errors are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: MPL Estimation Considering Homogeneity in the Philippines (2014 and 2018)

	Participants in 2014				
Deep Parameter	δ	ν	β	$\tilde{\alpha}$	μ
	0.994***	0.253***	0.880***	0.320***	0.308***
	(0.00112)	(0.0471)	(0.0292)	(0.107)	(0.0501)

	Participants in 2018				
Deep Parameter	δ	ν	β	$\tilde{\alpha}$	μ
	0.997***	0.124***	0.913***	0.533***	0.220***
	(0.000581)	(0.0285)	(0.0216)	(0.0960)	(0.0448)

Notes: Individually clustered standard errors are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: CTB Estimation Considering LC in the Philippines (2014)

	(1) NLS with CTB
β	0.684***
	(0.0363)
δ	0.994***
	(0.000677)
α	0.163***
	(0.0127)
τ_0	0.161***
	(0.0324)
τ_1	-0.000000110**
	(4.53e-08)
Observations	3768

Notes: Individually clustered standard errors are reported in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 19: CTB Estimation Considering LC in the Philippines (2018)

	(1)
	NLS with CTB
β	0.732***
	(0.0394)
δ	0.995***
	(0.000676)
α	0.142***
	(0.0119)
τ_0	0.178***
	(0.0398)
τ_1	1.67e-08
	(7.01e-08)
Observations	3,384

Notes: Individually clustered standard errors are reported in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 1: Summary of Raw Data (CTB in 2014) in Japan

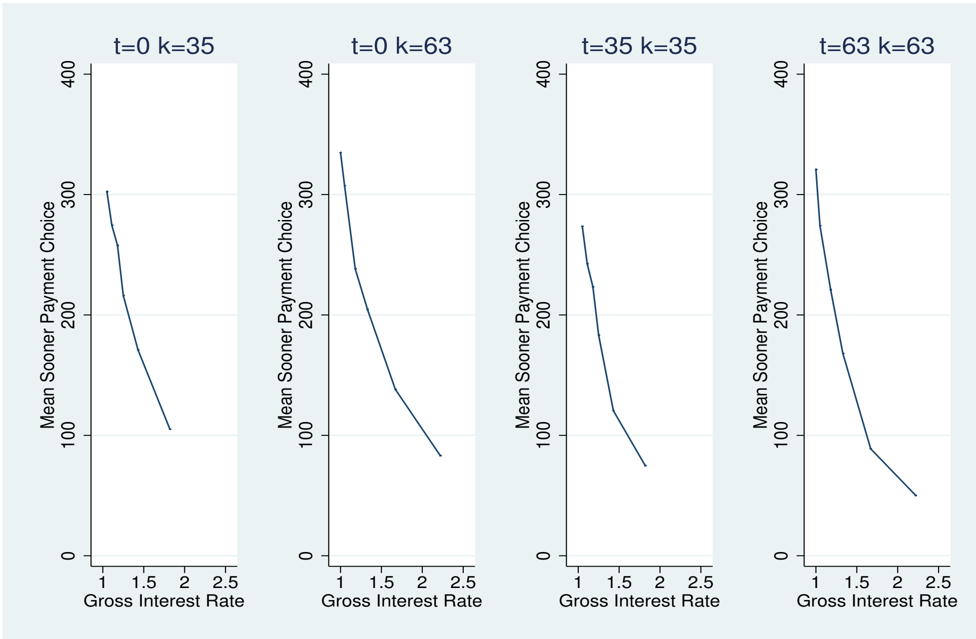


Figure 2: Summary of Raw Data (CTB in 2017) in Japan

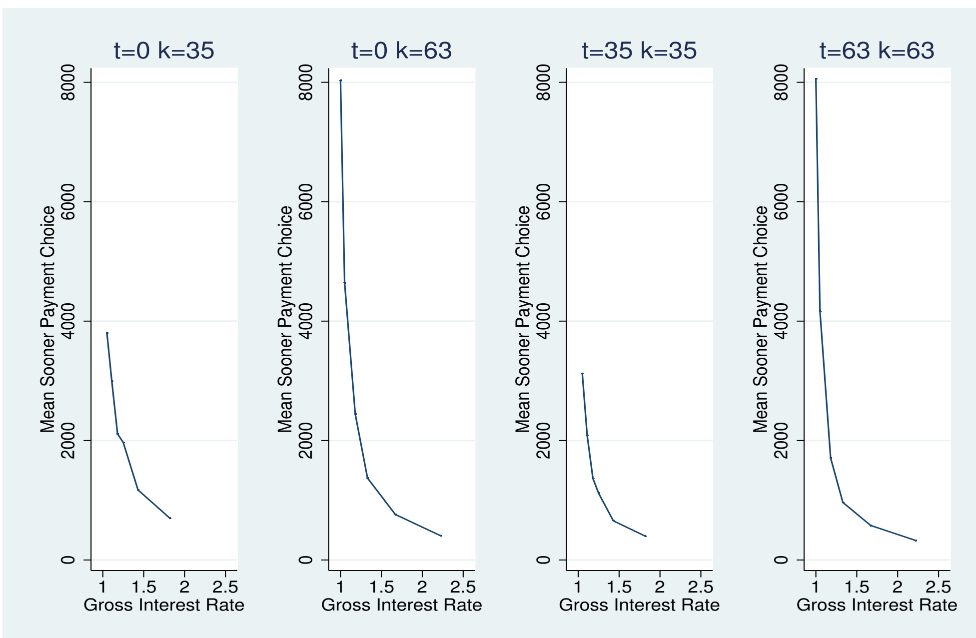


Figure 3: Summary of Raw Data (MPL) in Japan

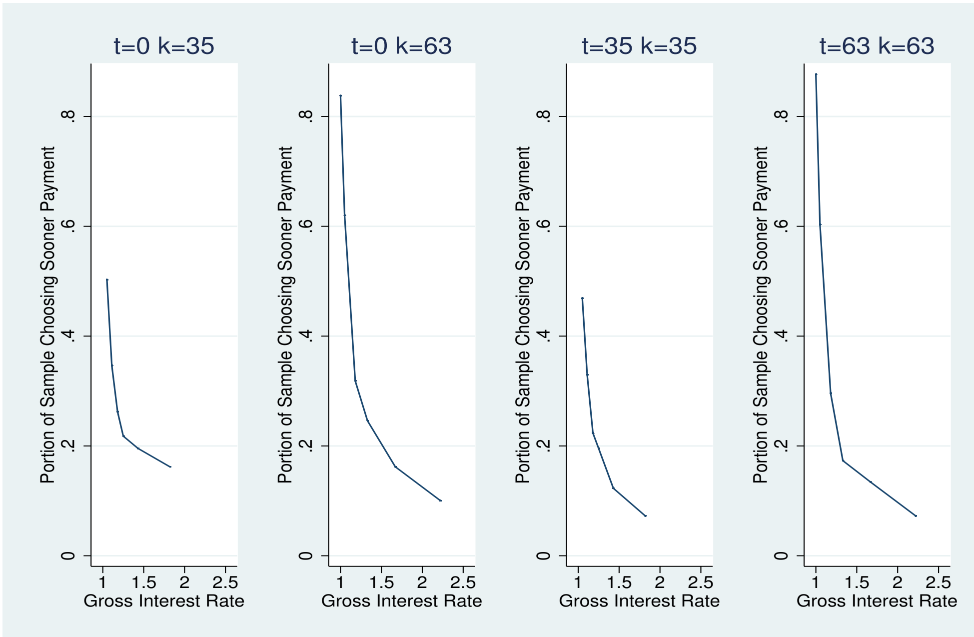


Figure 4: Summary of Raw Data (HL) in Japan

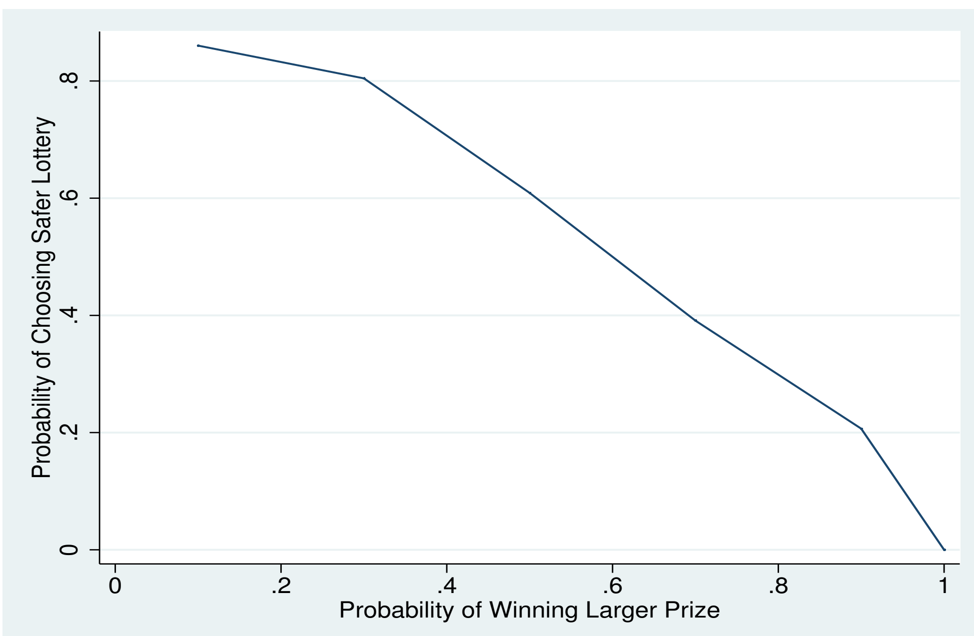


Figure 5: Summary of Raw Data Considering for House Damages (CTB in 2014) in Japan

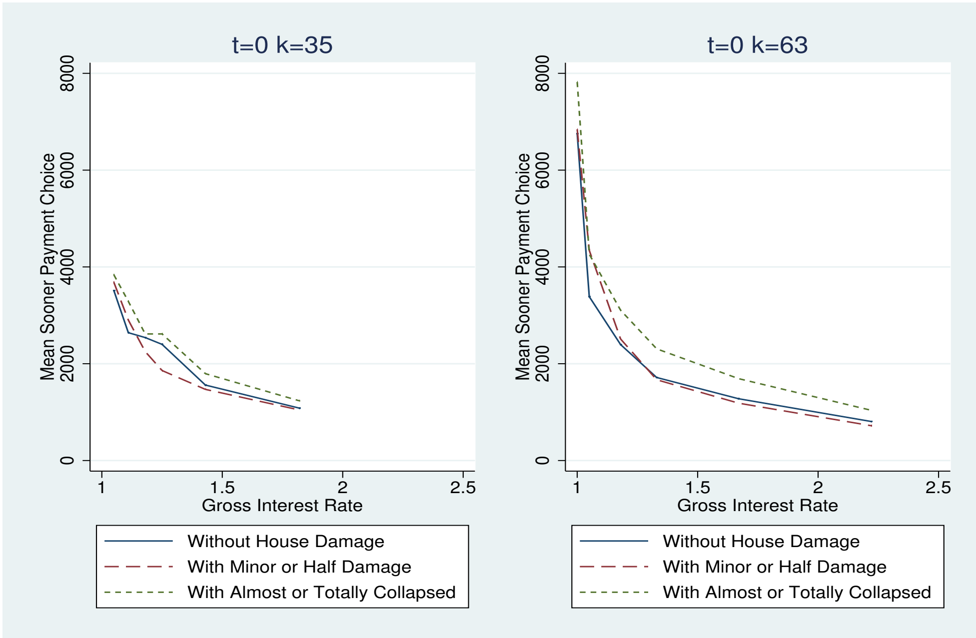


Figure 6: Summary of Raw Data Considering for House Damages (CTB in 2014) in Japan

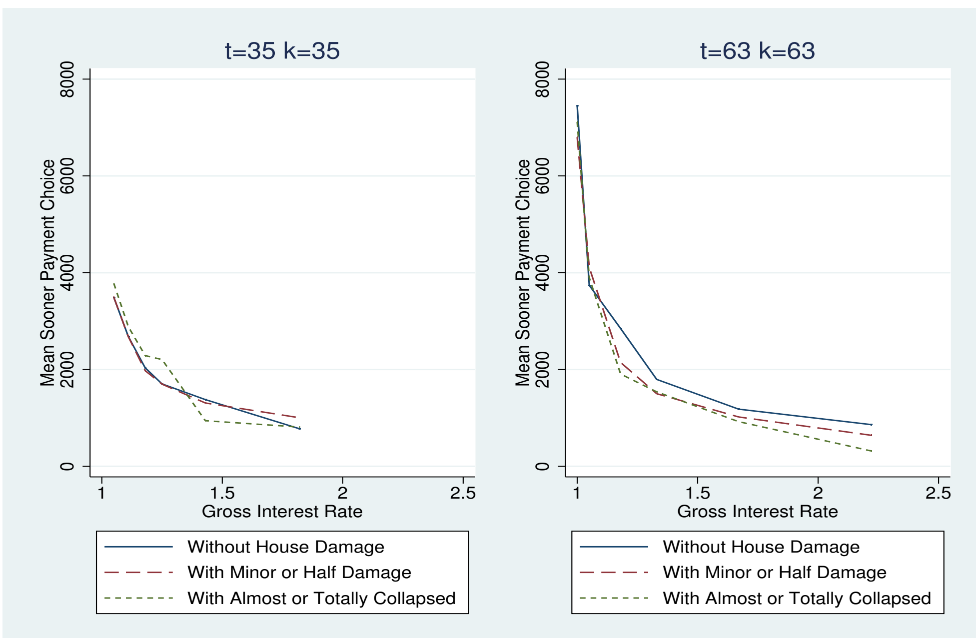


Figure 7: Summary of Raw Data Considering for House Damages (CTB in 2017) in Japan

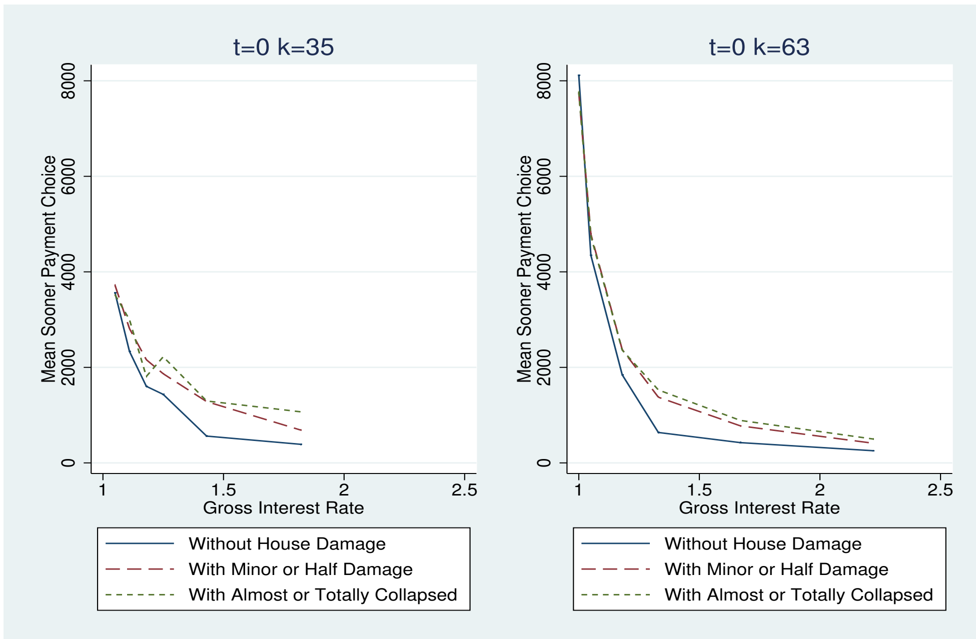


Figure 8: Summary of Raw Data Considering for House Damages (CTB in 2017) in Japan

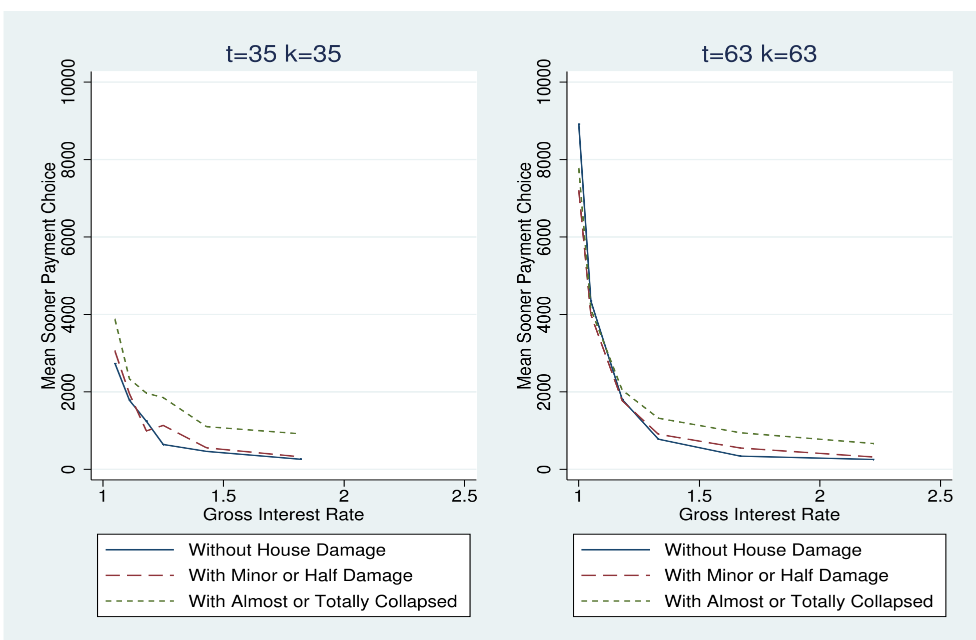


Figure 9: Summary of Raw Data Considering for House Damages (MPL) in Japan

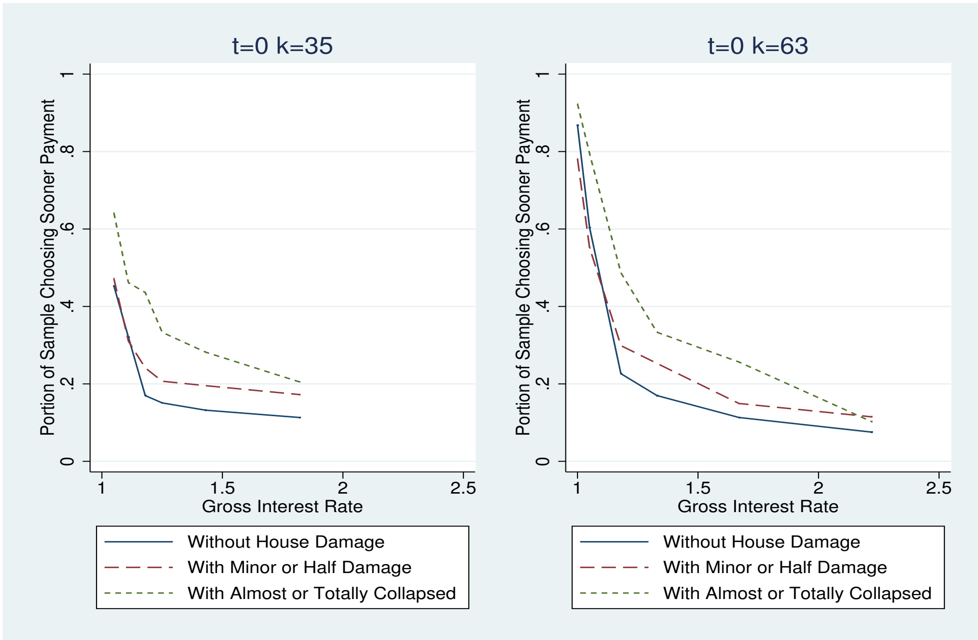


Figure 10: Summary of Raw Data Considering for House Damages (MPL) in Japan

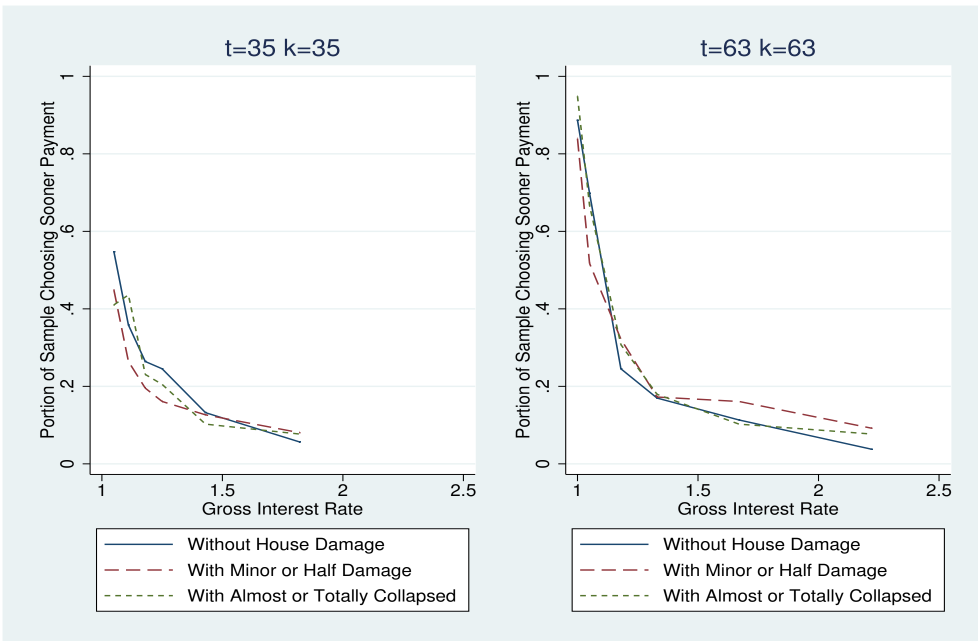


Figure 11: Summary of Raw Data Considering for House Damages (HL) in Japan

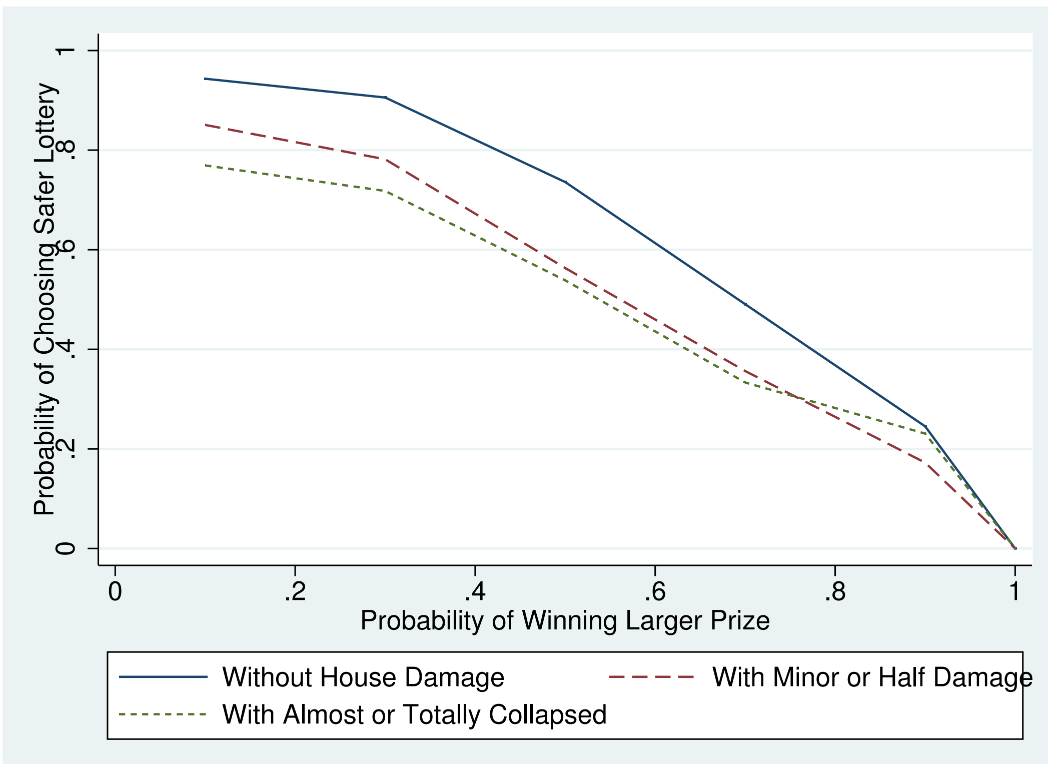


Figure 12: Summary of Raw Data (CTB in 2014) in the Philippines

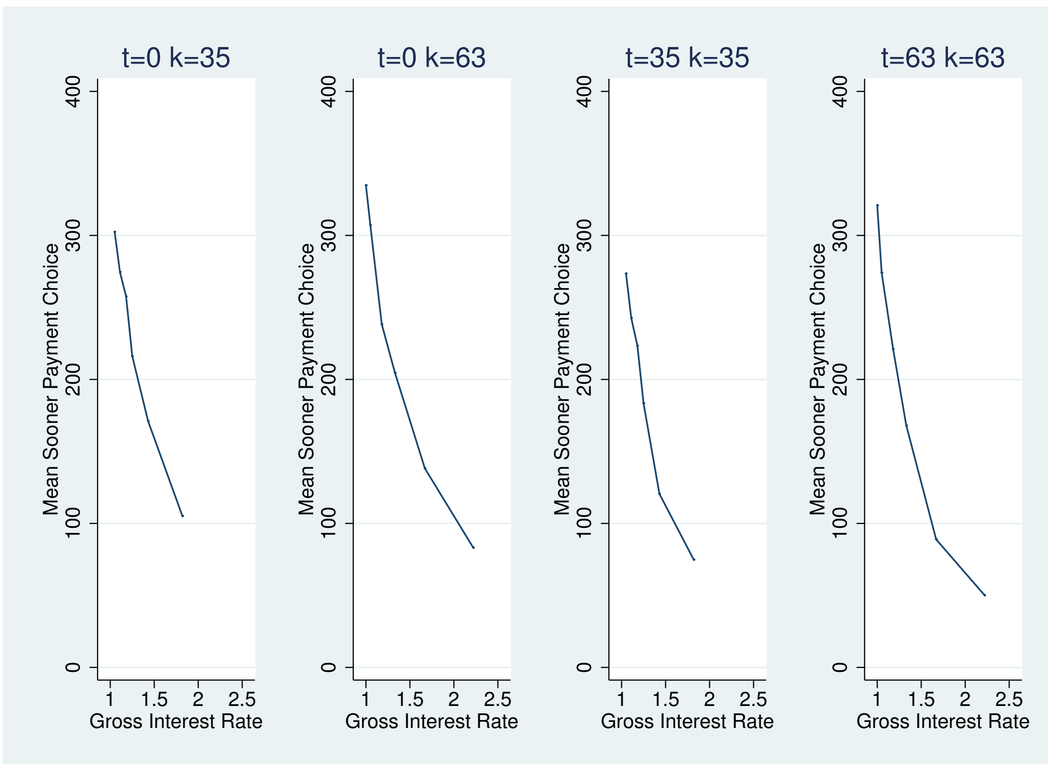


Figure 13: Summary of Raw Data (MPL in 2014) in the Philippines

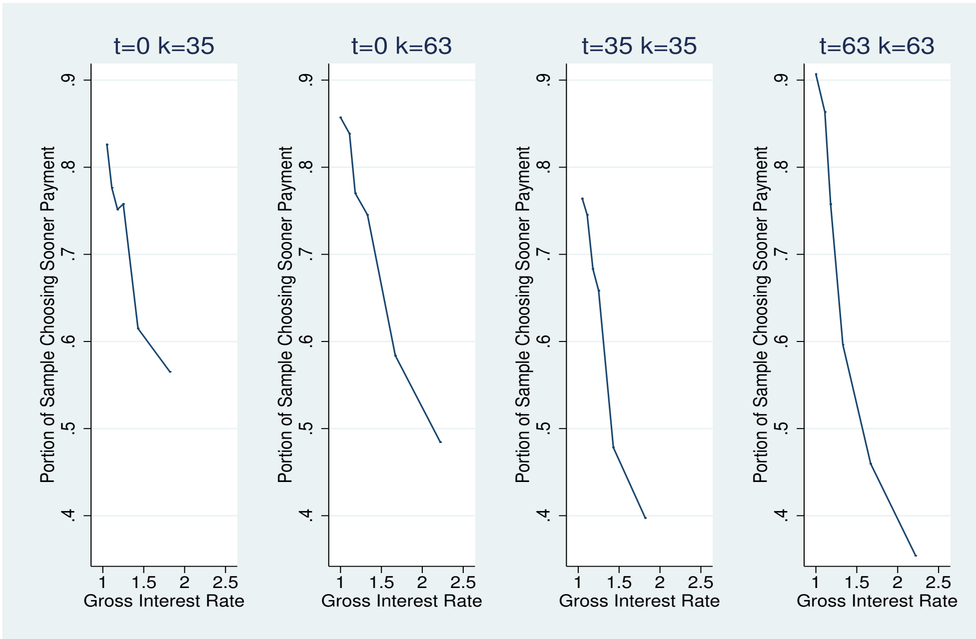


Figure 14: Summary of Raw Data (HL in 2014) in the Philippines

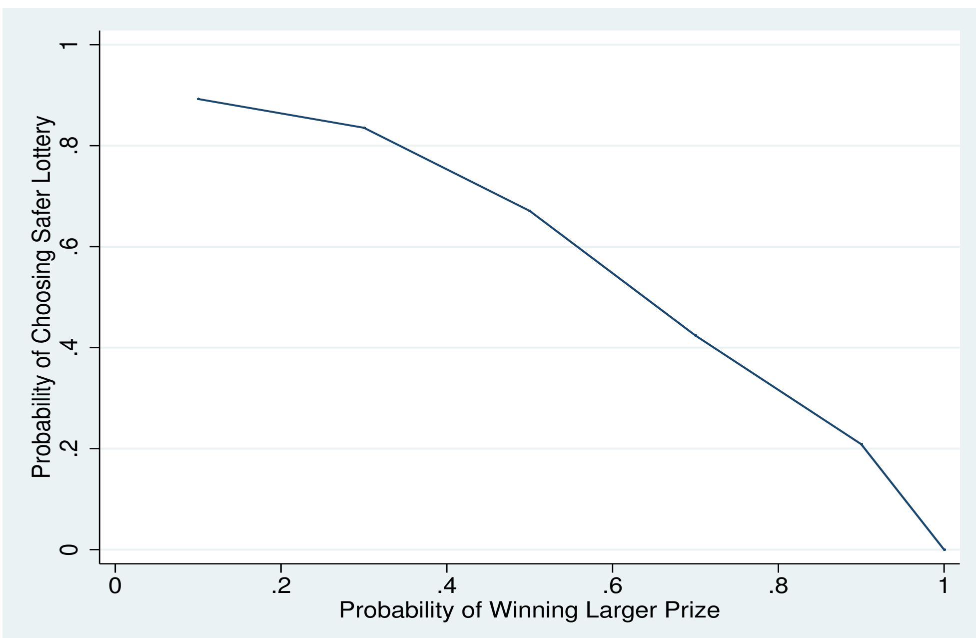


Figure 15: Summary of Raw Data Considering for Satellite Farm Damage (CTB in 2014) in the Philippines

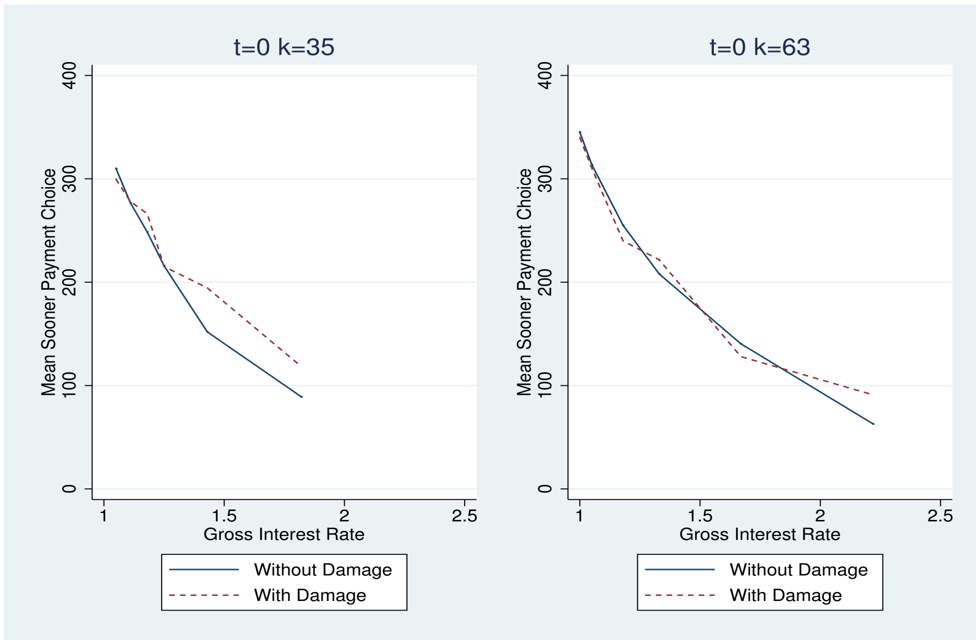


Figure 16: Summary of Raw Data Considering for Satellite Farm Damage (CTB in 2014) in the Philippines

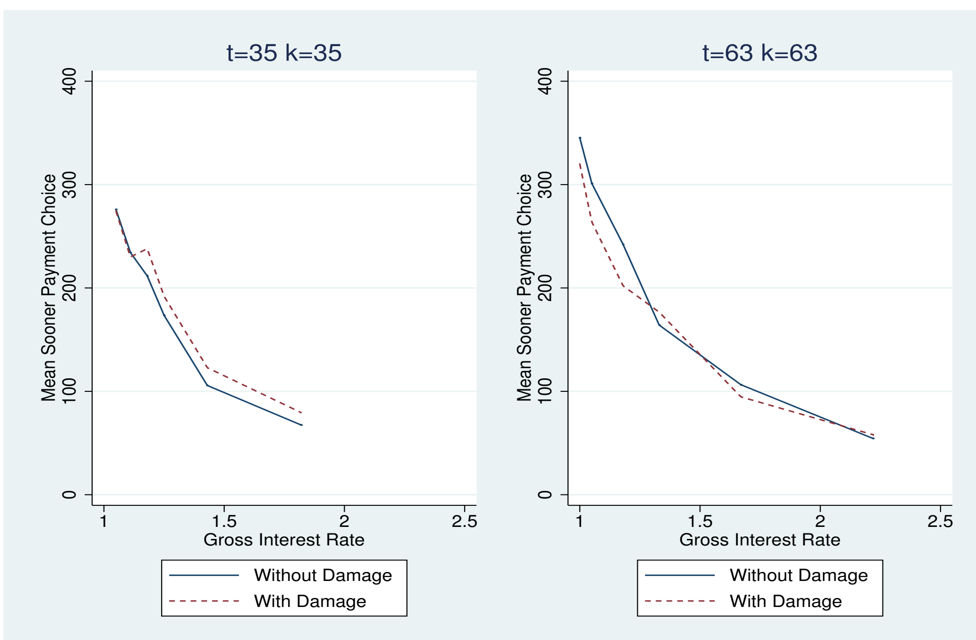


Figure 17: Summary of Raw Data Considering for Our Defined Damage (CTB in 2014) in the Philippines

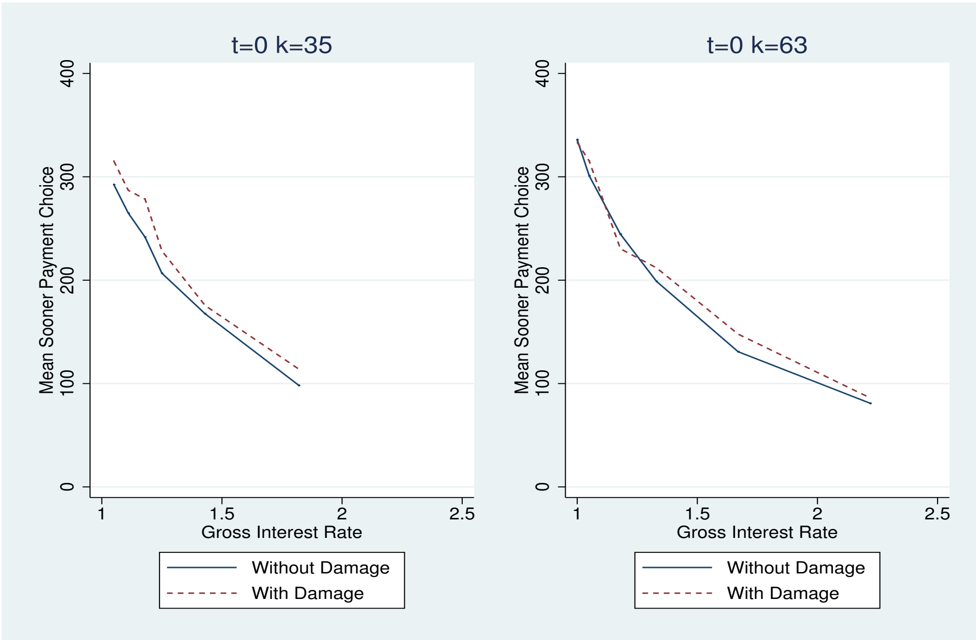


Figure 18: Summary of Raw Data Considering for Our Defined Damage (CTB in 2014) in the Philippines

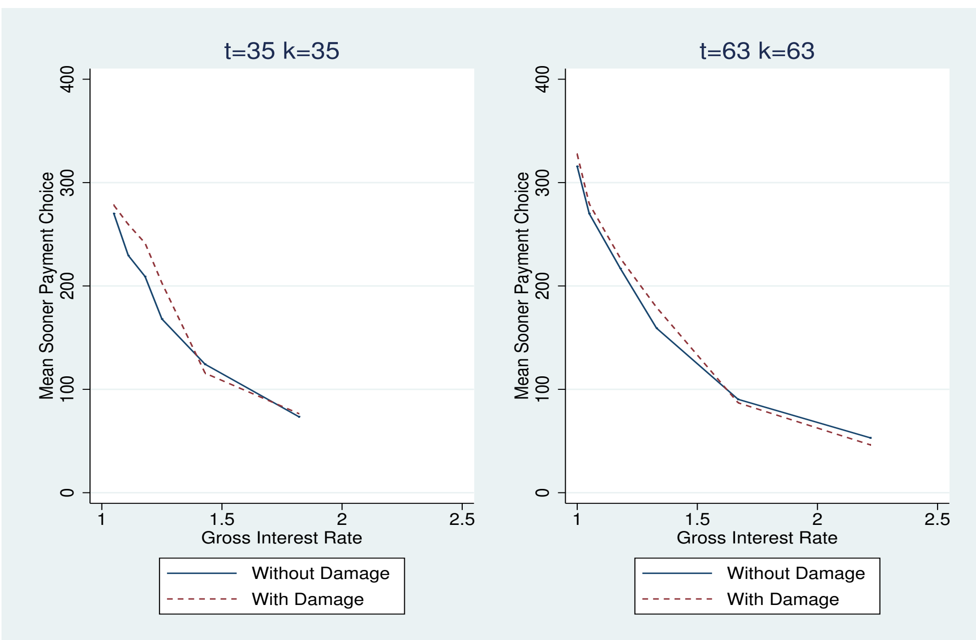


Figure 19: Summary of Raw Data Considering for Our Defined Damage Combined With Satellite Farm Damage (CTB in 2014) in the Philippines

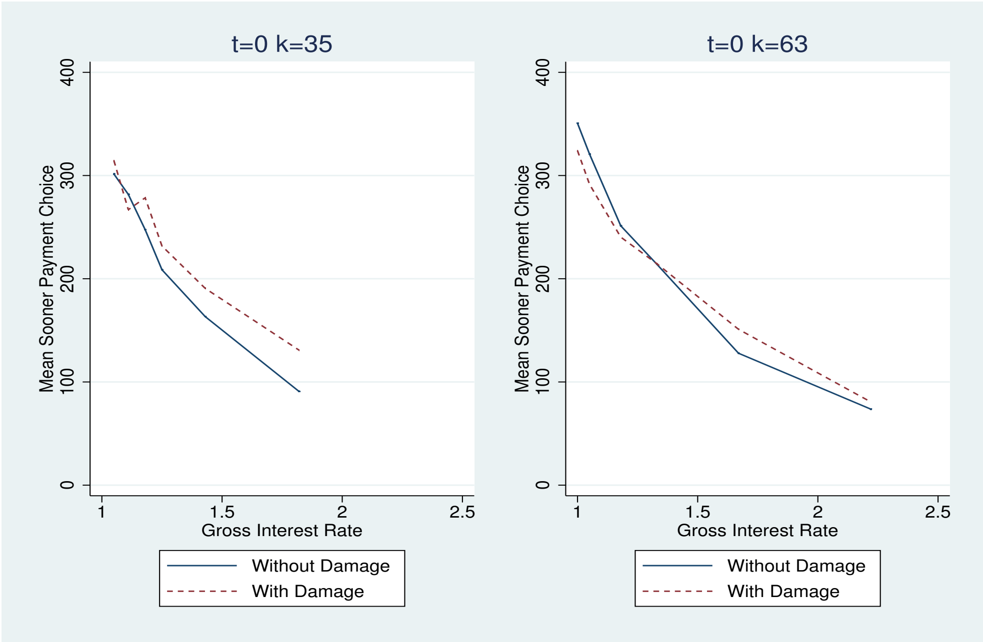


Figure 20: Summary of Raw Data Considering for Our Defined Damage Combined With Satellite Farm Damage (CTB in 2014) in the Philippines

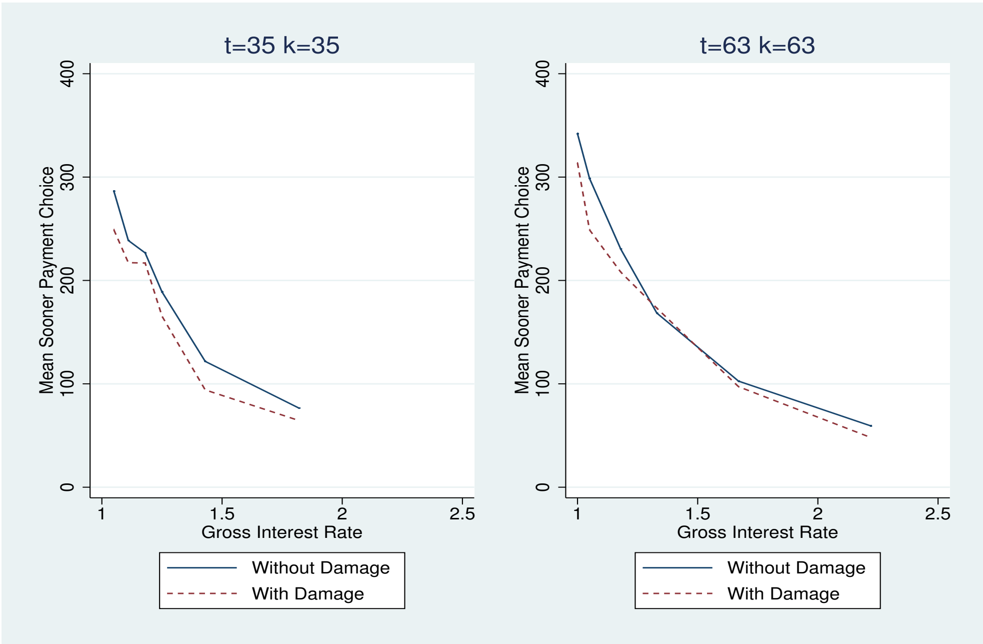


Figure 21: Summary of Raw Data Considering for Satellite Farm Damage (MPL in 2014) in the Philippines

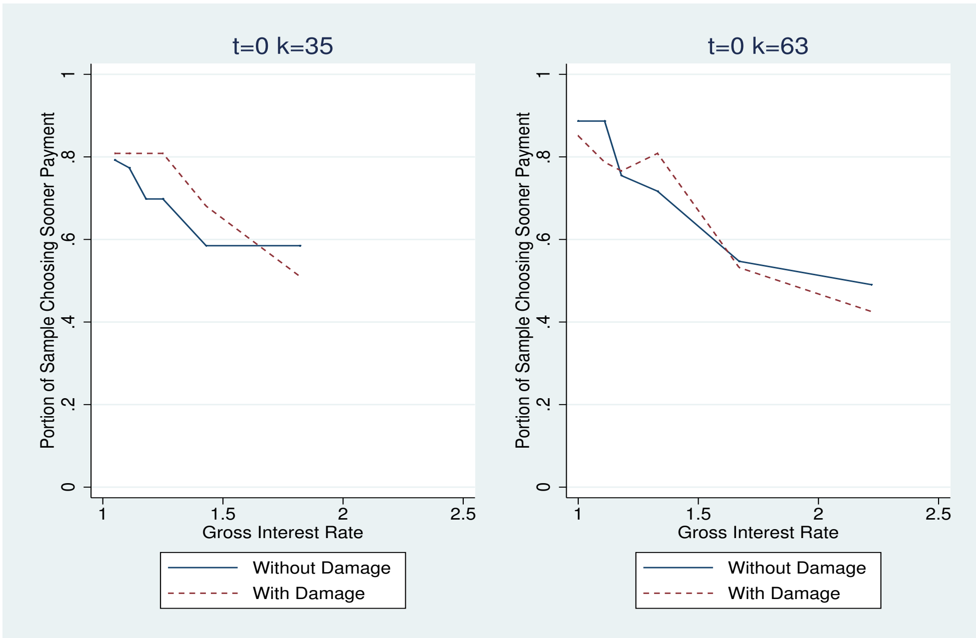


Figure 22: Summary of Raw Data Considering for Satellite Farm Damage (MPL in 2014) in the Philippines

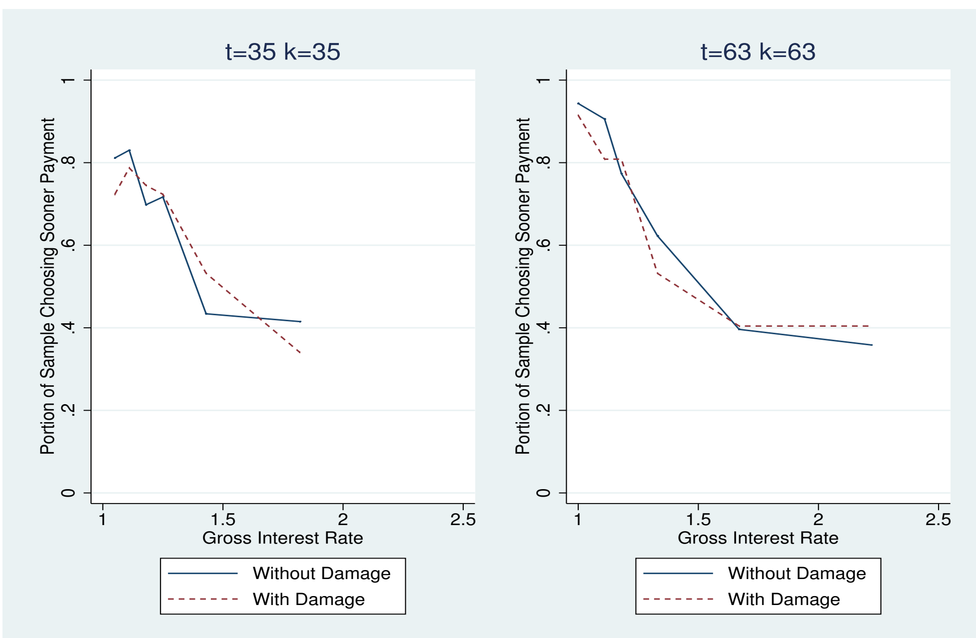


Figure 23: Summary of Raw Data Considering for Our Defined Damage (MPL in 2014) in the Philippines

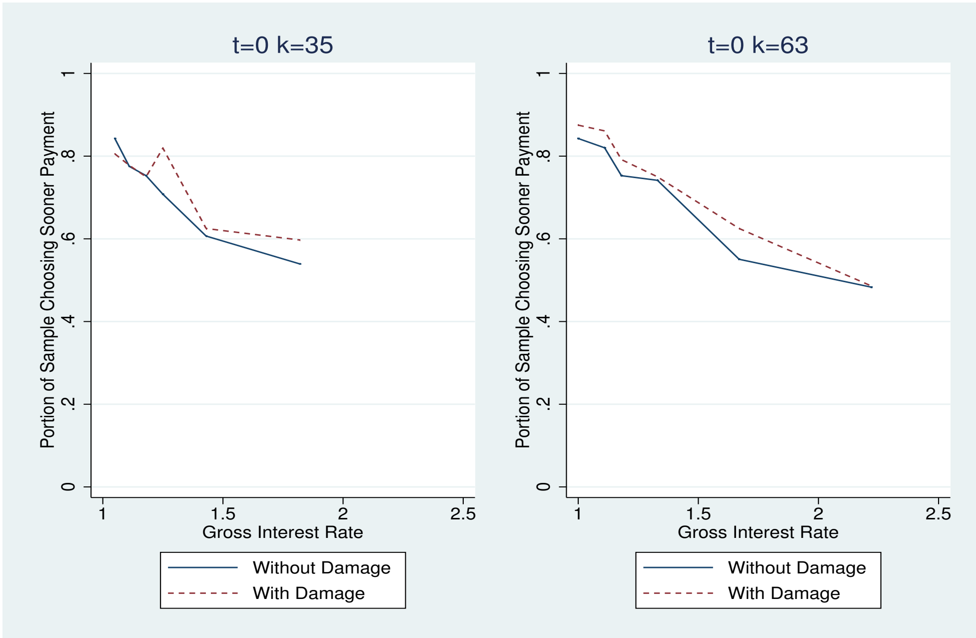


Figure 24: Summary of Raw Data Considering for Our Defined Damage (MPL in 2014) in the Philippines

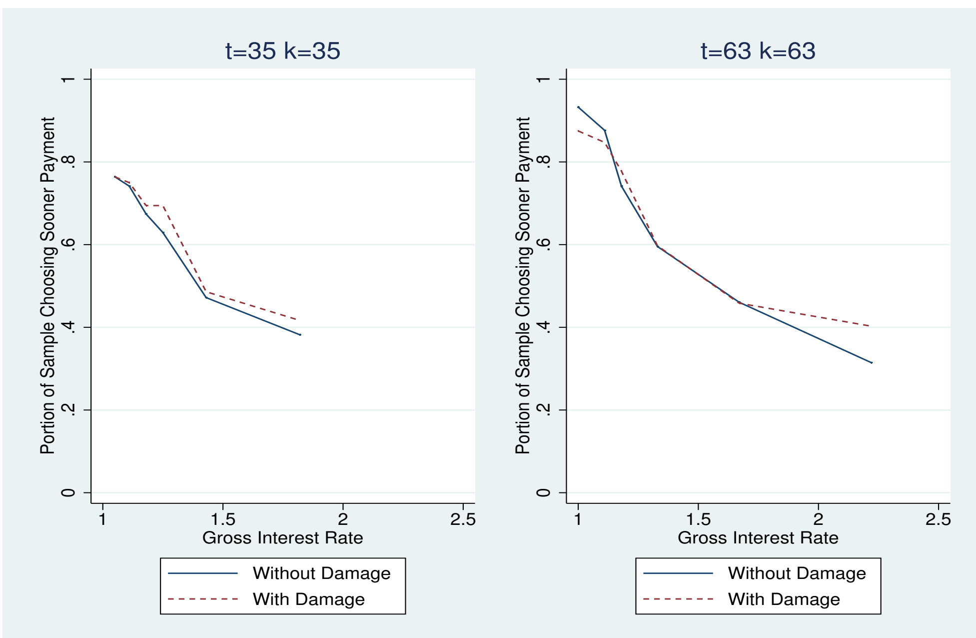


Figure 25: Summary of Raw Data Considering for Our Defined Damage Combined With Satellite Farm Damage (MPL in 2014) in the Philippines

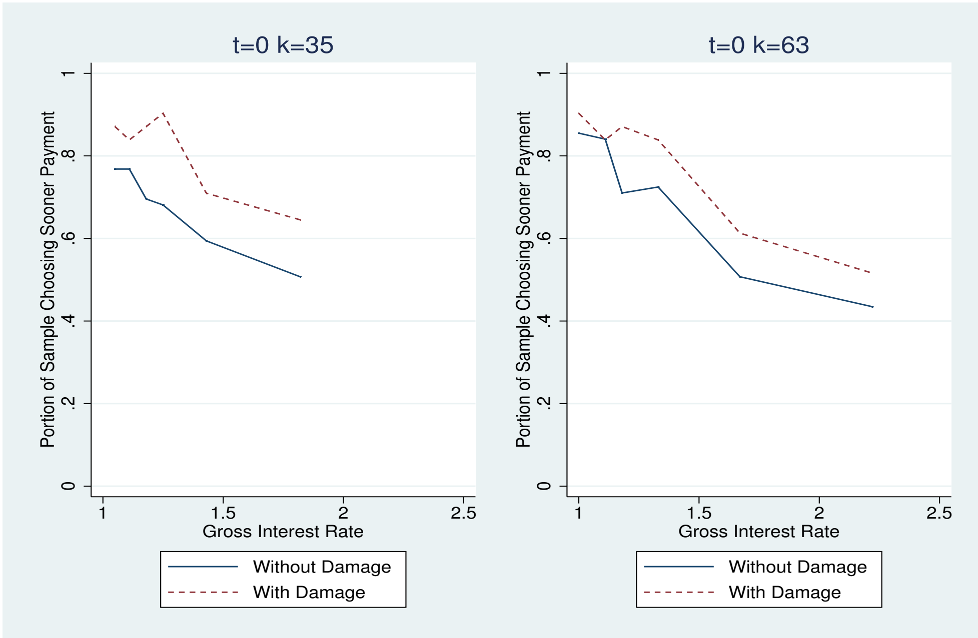


Figure 26: Summary of Raw Data Considering for Our Defined Damage Combined With Satellite Farm Damage (MPL in 2014) in the Philippines

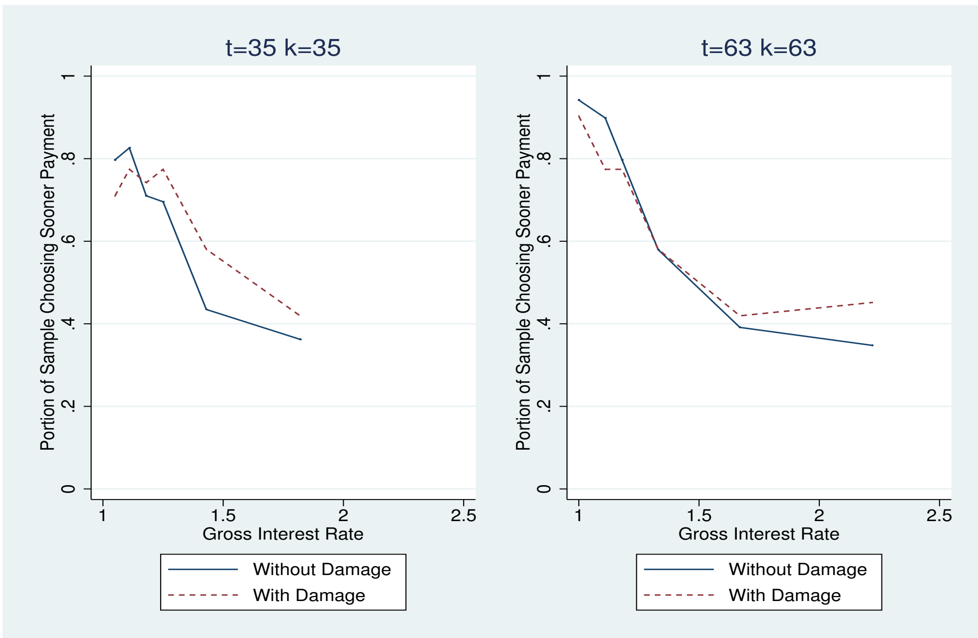


Figure 27: Summary of Raw Data Considering for Satellite Farm Damage (HL in 2014) in the Philippines

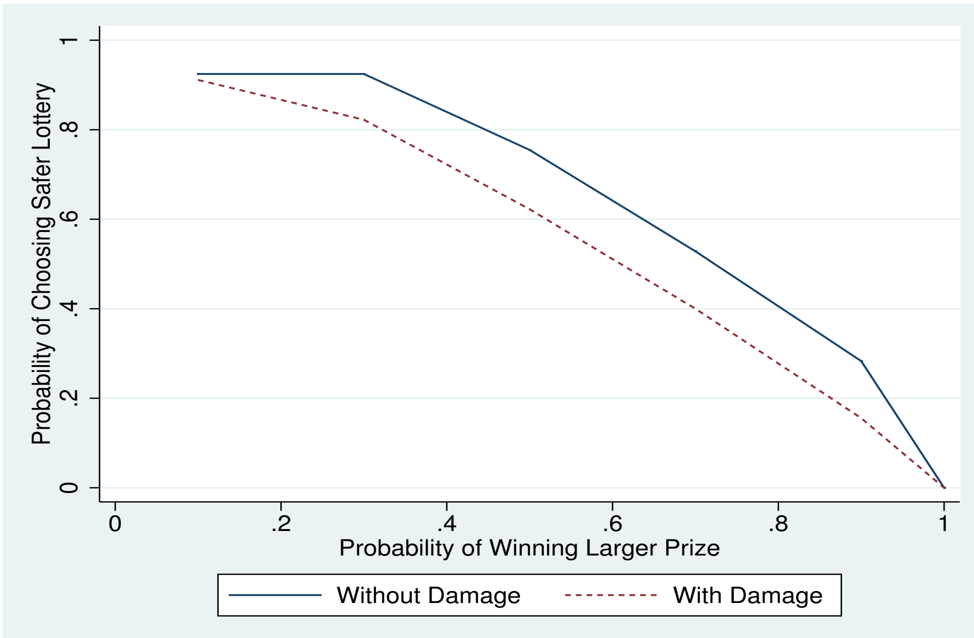


Figure 28: Summary of Raw Data Considering for Our Defined Damage (HL in 2014) in the Philippines

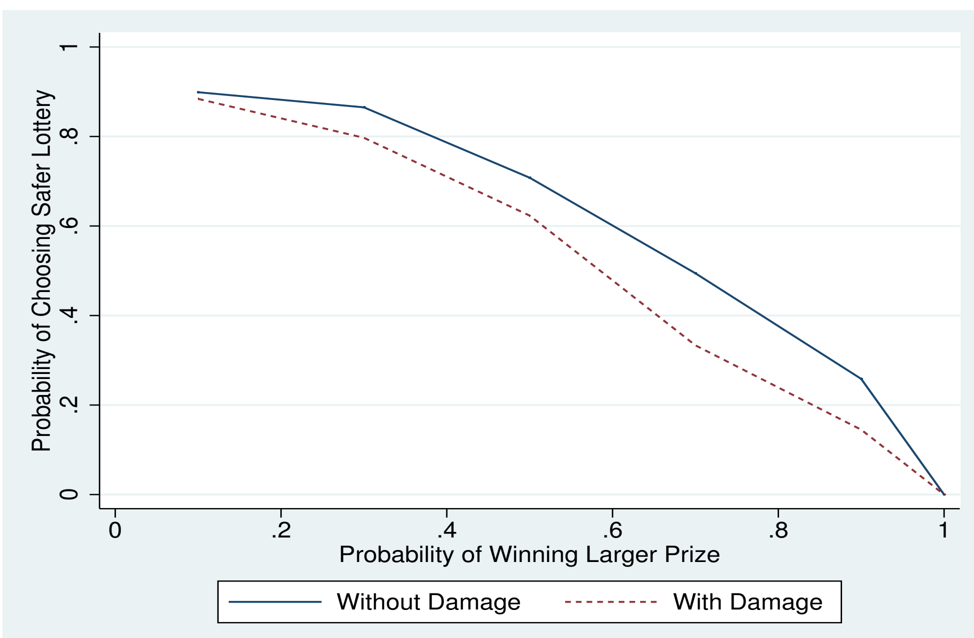


Figure 29: Summary of Raw Data Considering for Our Defined Damage Combined With Satellite Farm Damage (HL in 2014) in the Philippines

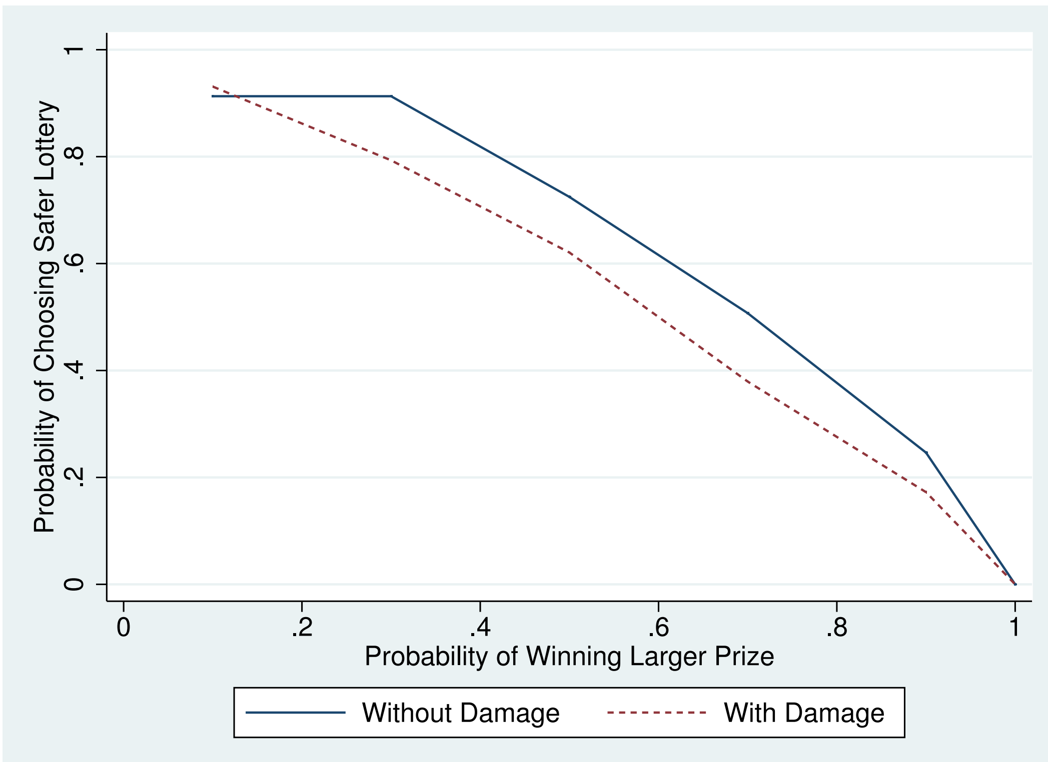


Figure 30: Summary of Raw Data (CTB in 2018) in the Philippines

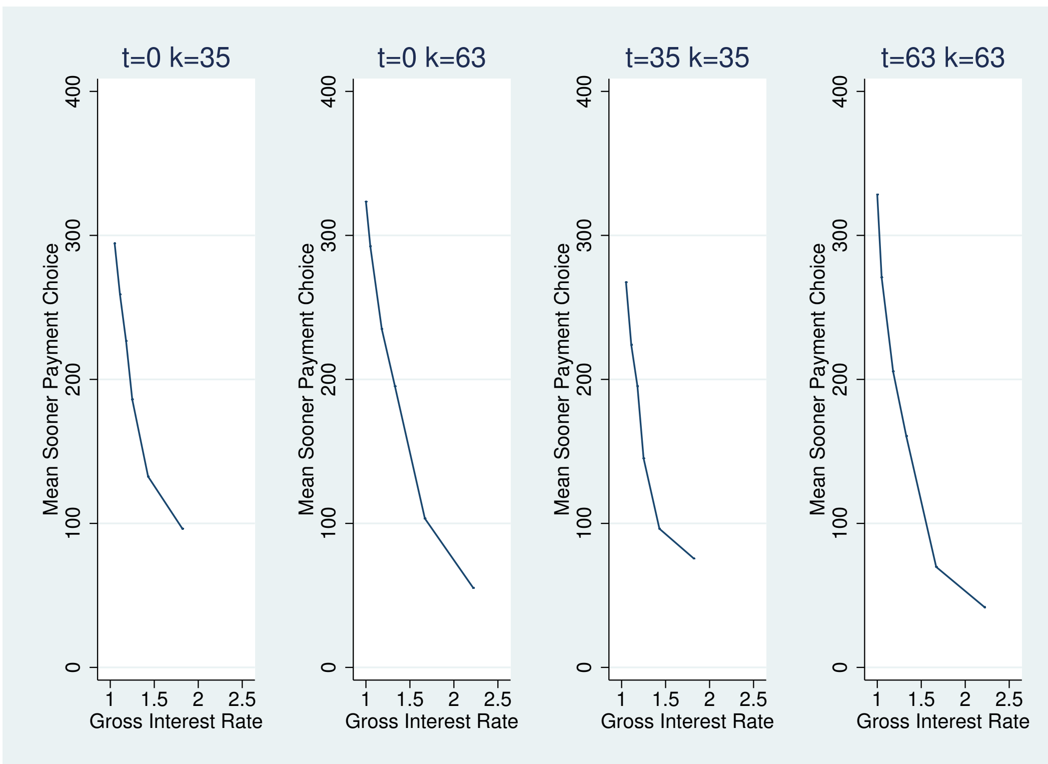


Figure 31: Summary of Raw Data (MPL in 2018) in the Philippines

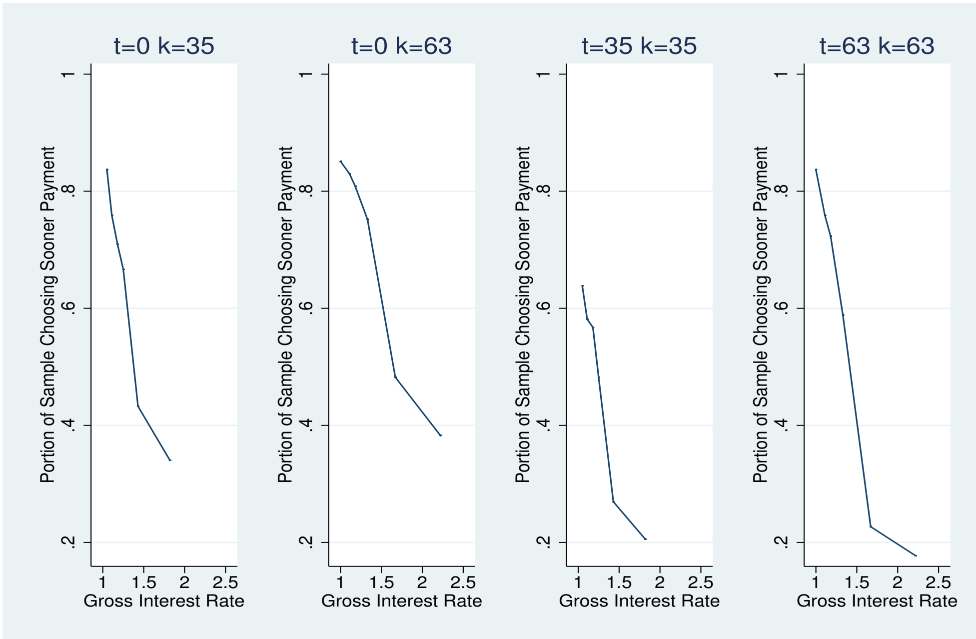


Figure 32: Summary of Raw Data (HL in 2018) in the Philippines

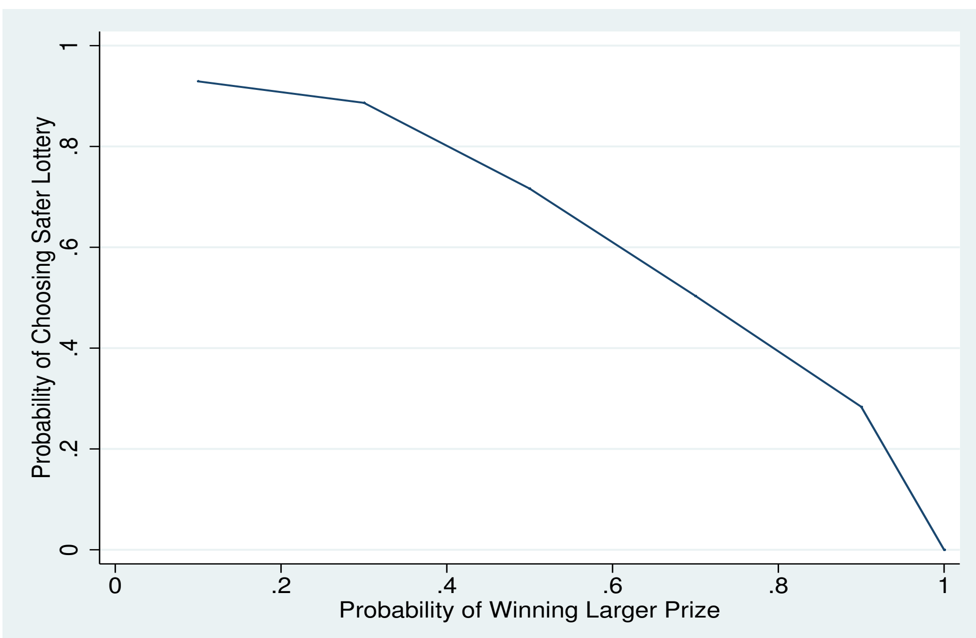


Figure 33: Summary of Raw Data Considering for Satellite Farm Damage (CTB in 2018) in the Philippines

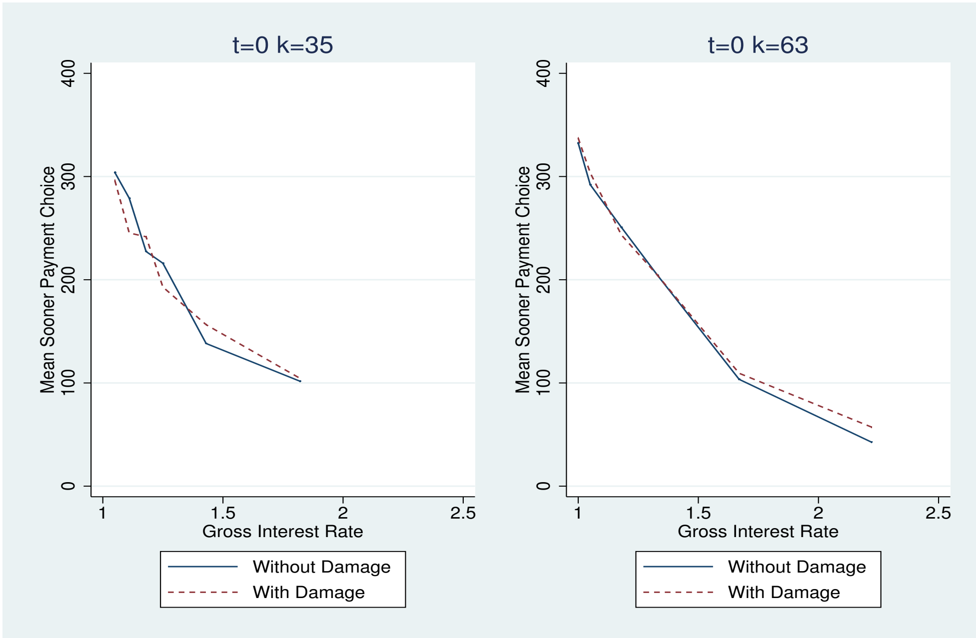


Figure 34: Summary of Raw Data Considering for Satellite Farm Damage (CTB in 2018) in the Philippines

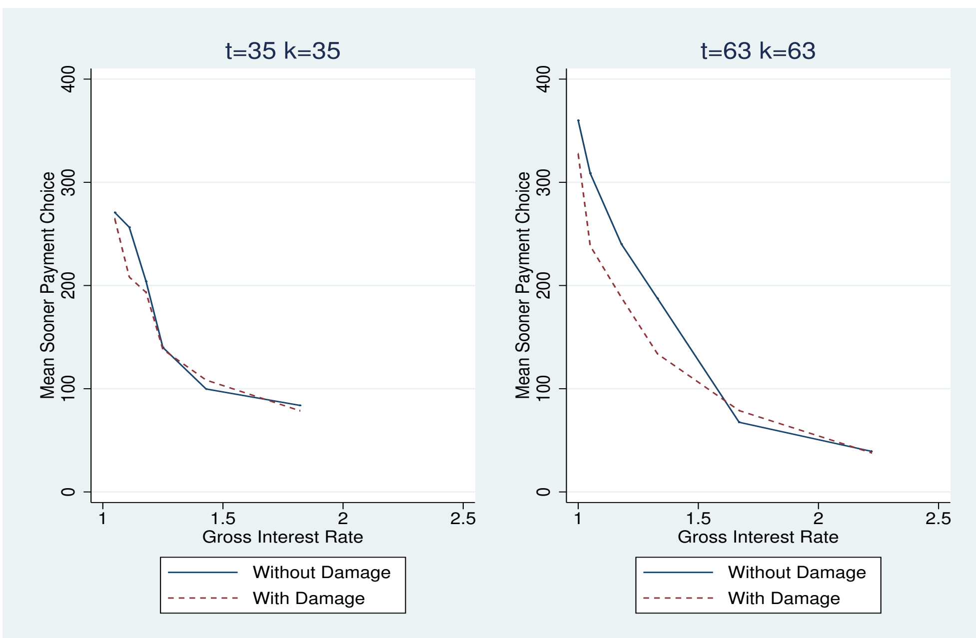


Figure 35: Summary of Raw Data Considering for Our Defined Damage (CTB in 2018) in the Philippines

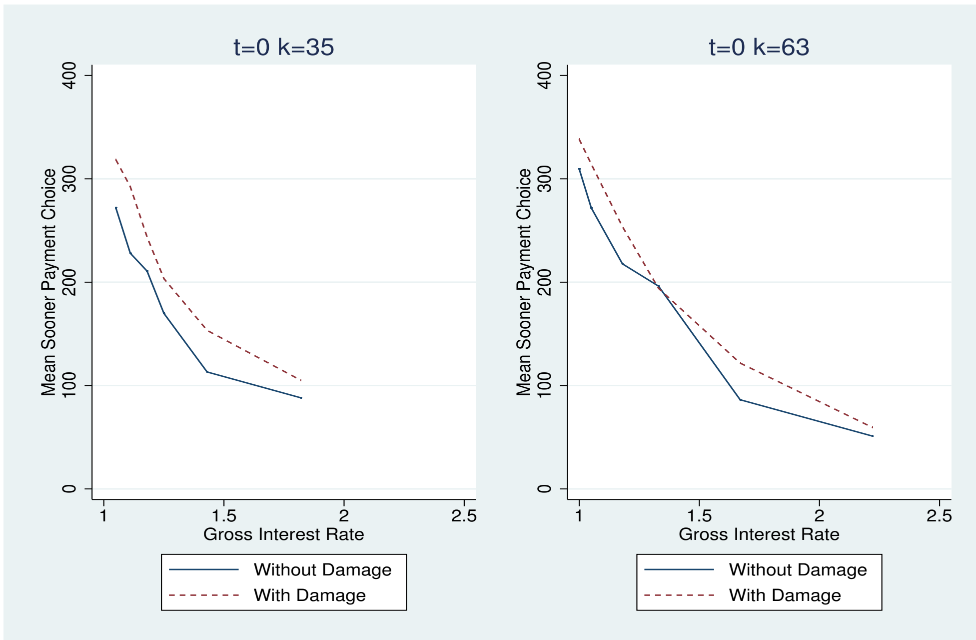


Figure 36: Summary of Raw Data Considering for Our Defined Damage (CTB in 2018) in the Philippines

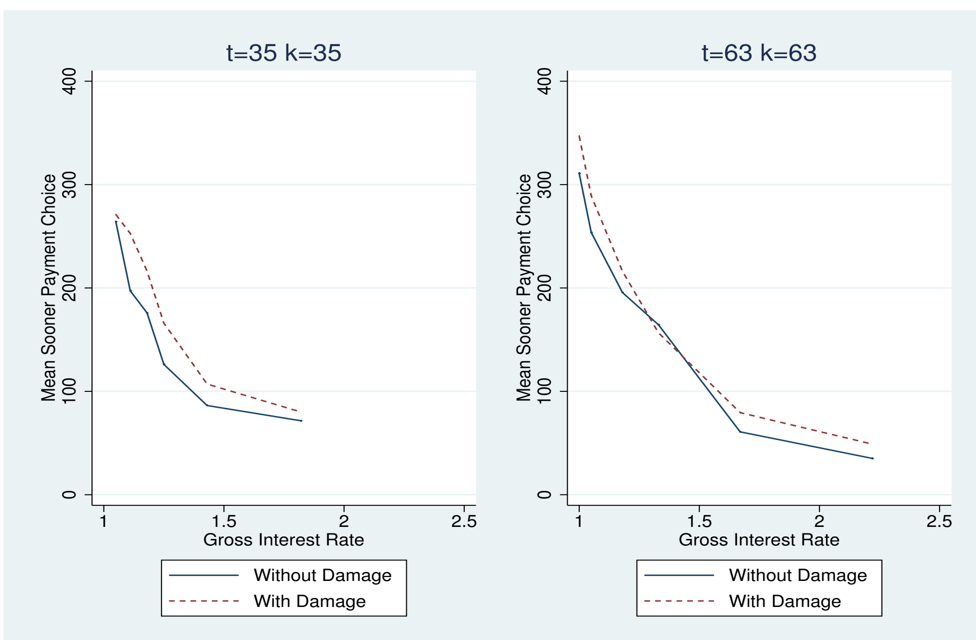


Figure 37: Summary of Raw Data Considering for Our Defined Damage Combined With Satellite Farm Damage (CTB in 2018) in the Philippines

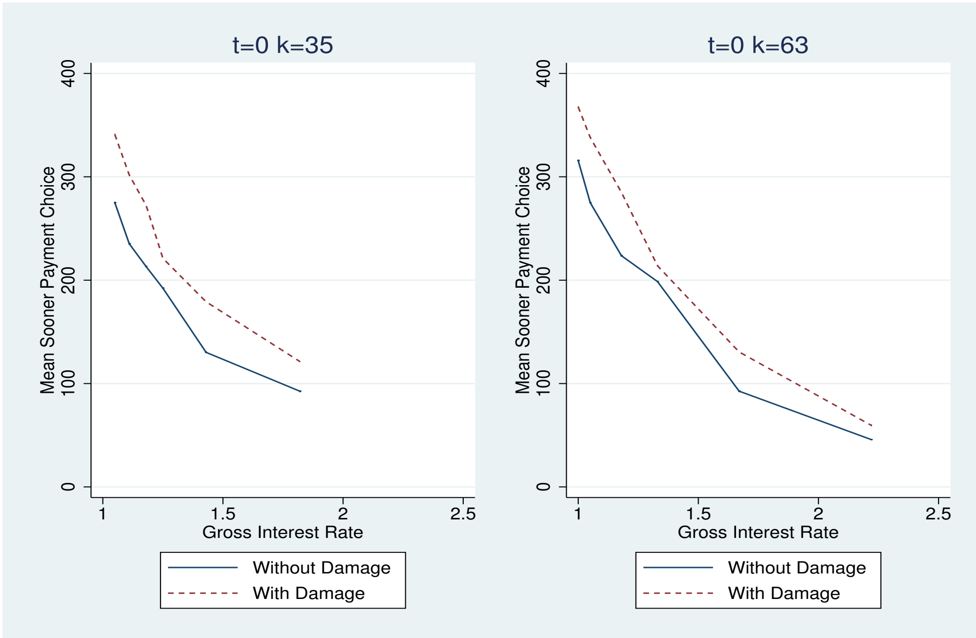


Figure 38: Summary of Raw Data Considering for Our Defined Damage Combined With Satellite Farm Damage (CTB in 2018) in the Philippines

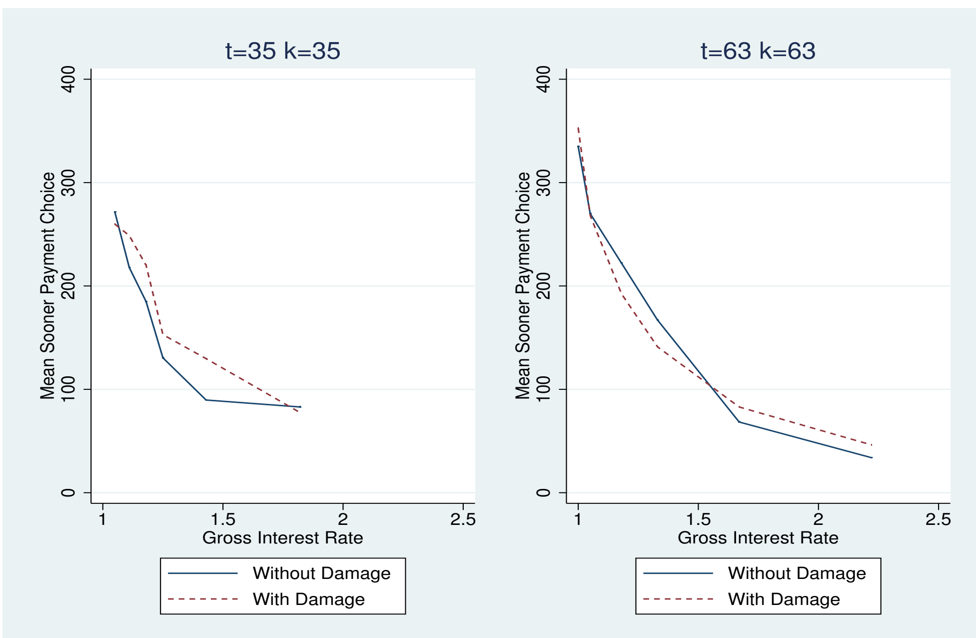


Figure 39: Summary of Raw Data Considering for Satellite Farm Damage (MPL in 2018) in the Philippines

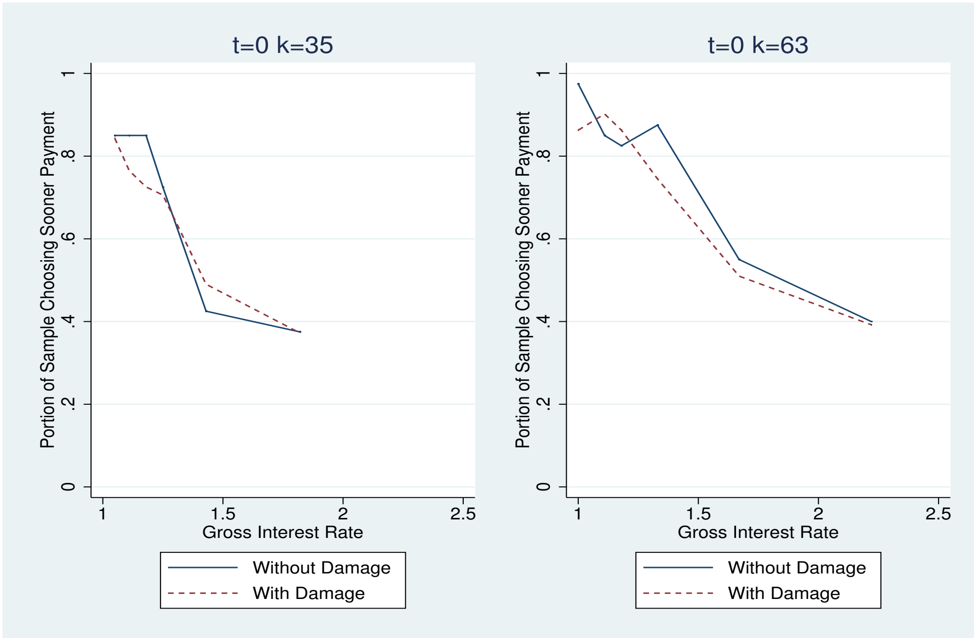


Figure 40: Summary of Raw Data Considering for Satellite Farm Damage (MPL in 2018) in the Philippines

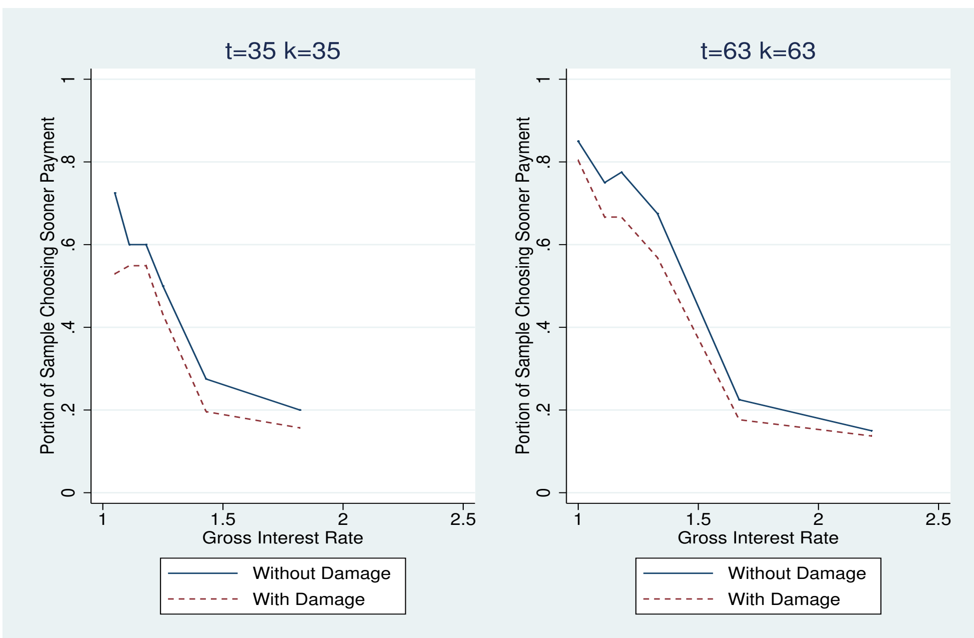


Figure 41: Summary of Raw Data Considering for Our Defined Damage (MPL in 2018) in the Philippines

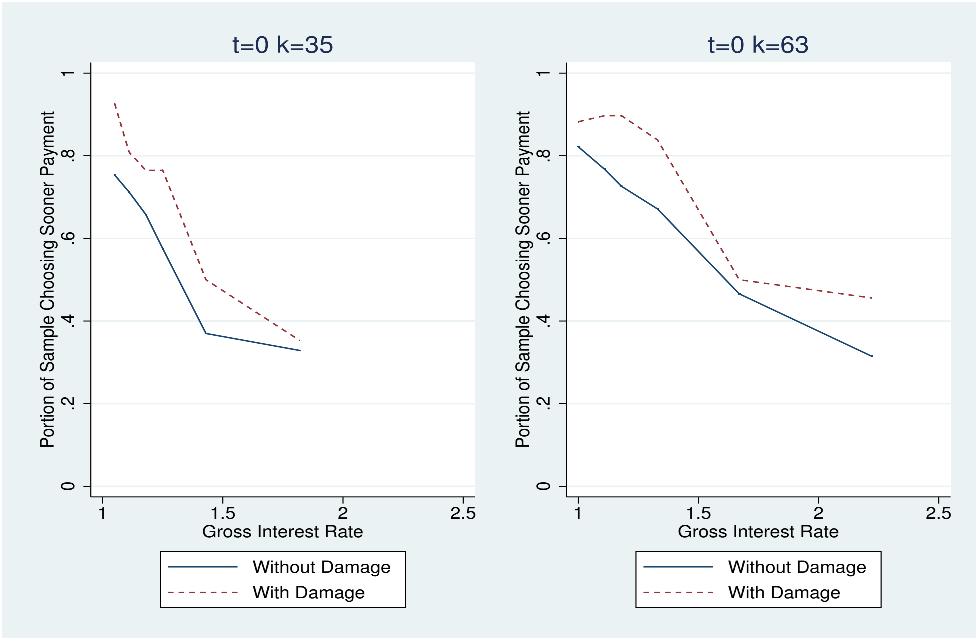


Figure 42: Summary of Raw Data Considering for Our Defined Damage (MPL in 2018) in the Philippines

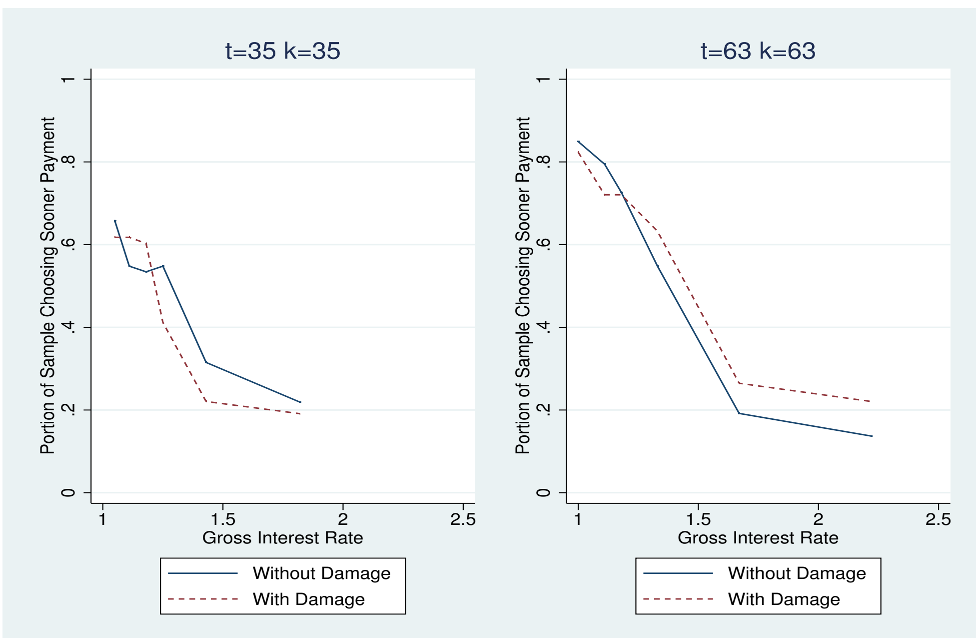


Figure 43: Summary of Raw Data Considering for Our Defined Damage Combined With Satellite Farm Damage (MPL in 2018) in the Philippines

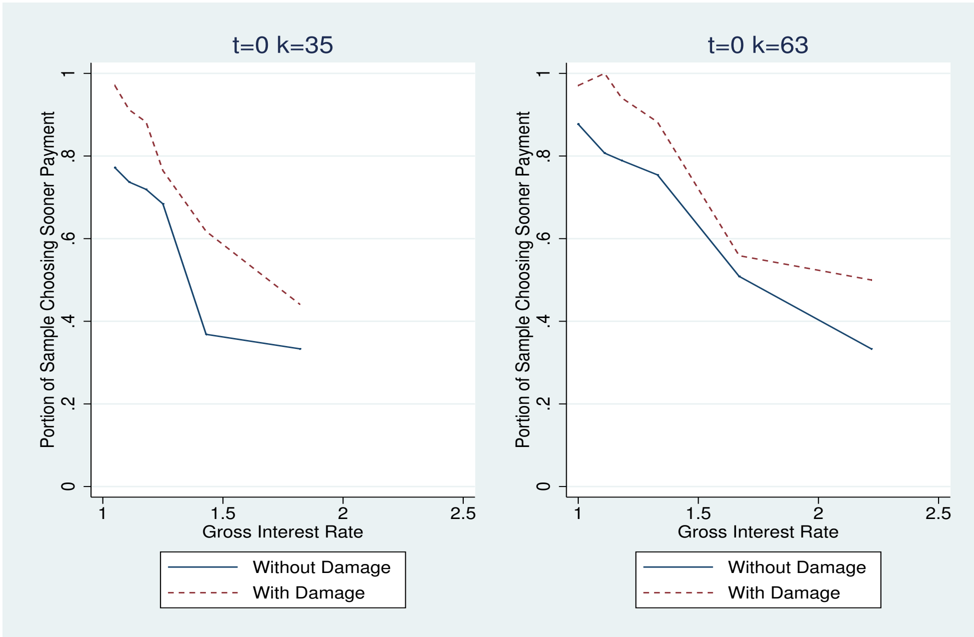


Figure 44: Summary of Raw Data Considering for Our Defined Damage Combined With Satellite Farm Damage (MPL in 2018) in the Philippines

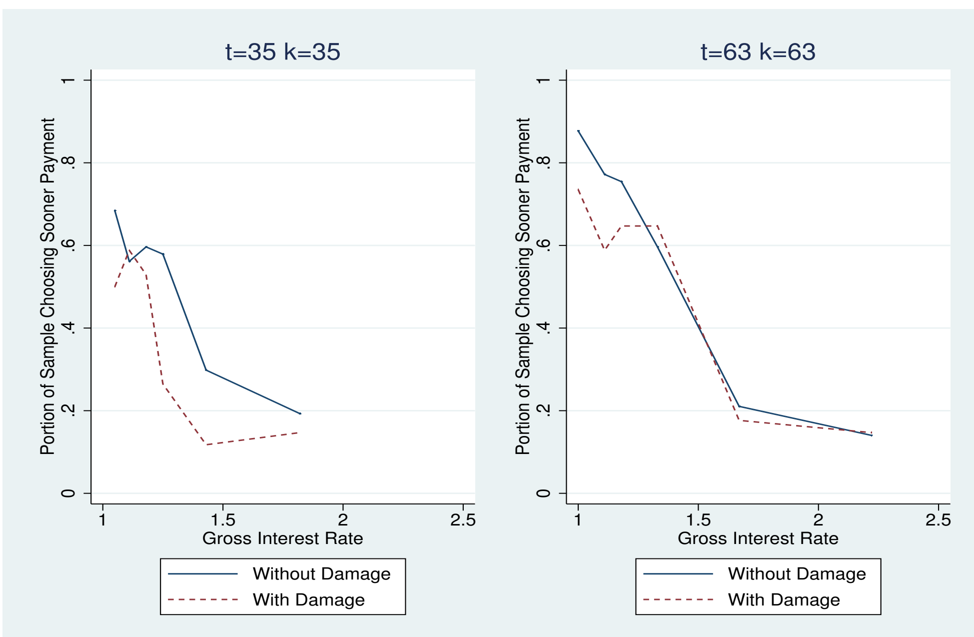


Figure 45: Summary of Raw Data Considering for Satellite Farm Damage (HL in 2018) in the Philippines

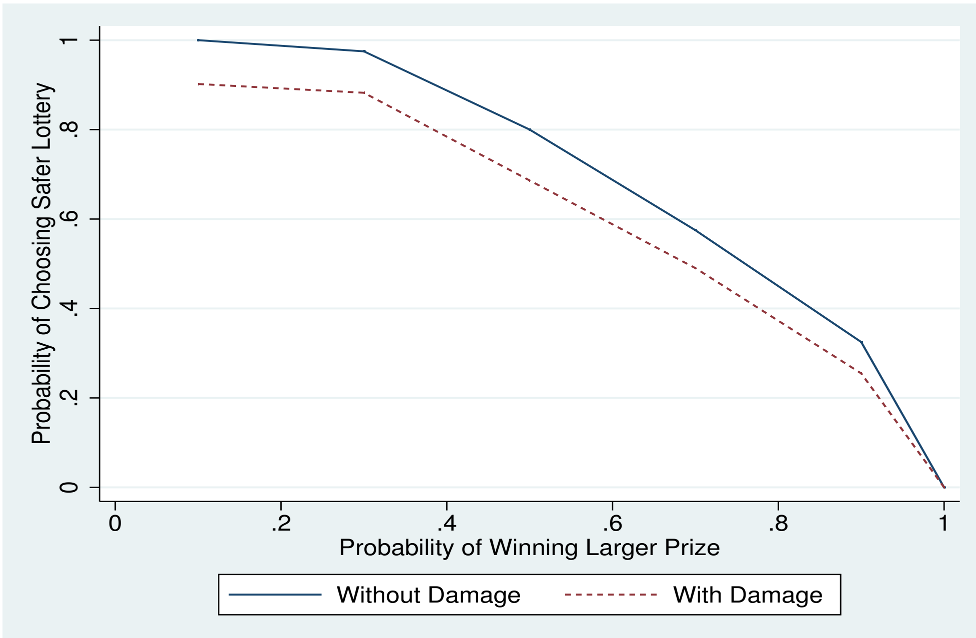


Figure 46: Summary of Raw Data Considering for Our Defined Damage (HL in 2018) in the Philippines

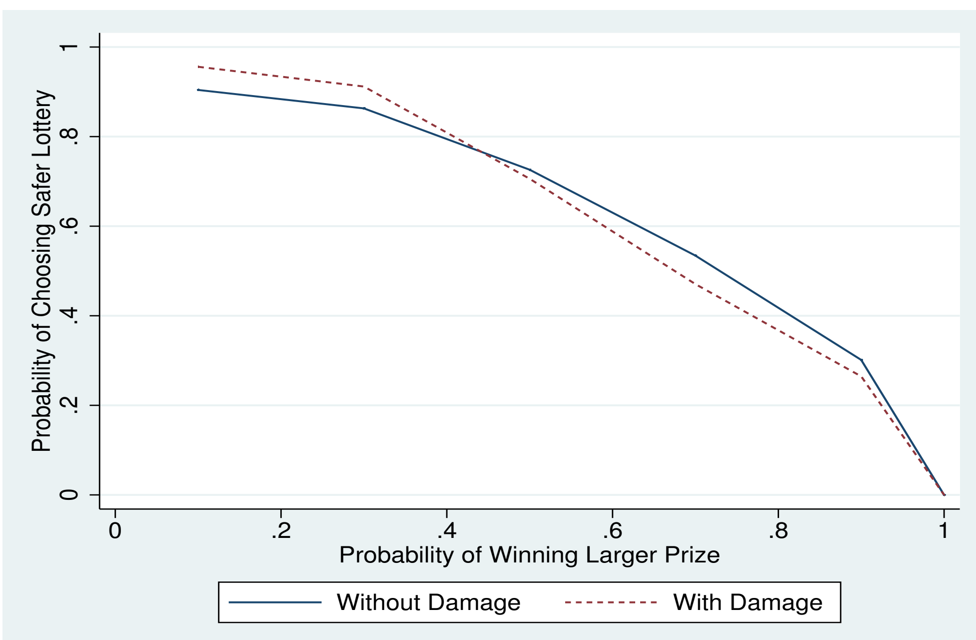


Figure 47: Summary of Raw Data Considering for Our Defined Damage Combined With Satellite Farm Damage (HL in 2018) in the Philippines