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Change in time preferences: Evidence from the Great East Japan Earthquake

Mika Akesaka

Institute of Social and Economic Research, Osaka University, 6-1, Mihogaoka, Ibaraki, Osaka 567-0047, Japan

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ABSTRACT

This study examines whether individuals' time preferences are affected by the damage caused by the tsunami resulting from the Great East Japan Earthquake of 2011 using panel surveys before and after the earthquake. When the change in time preferences is measured using the (β, δ) model, present bias tendency increases (shrinking β), although there is no statistically significant change in the time discount factor (δ) for those affected by the tsunami. The hyperbolic discounting dummy also shows an increase in time inconsistency. This change persists even five years after the earthquake.

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1. Introduction

Time preferences are an important factor for determining individuals' intertemporal choices in their daily lives, including consumption and savings. In traditional economics, individuals' time discount rates have been assumed to be constant under both the short- and long-term horizons and also stable over their lives. However, behavioral economists point out that some individuals follow a hyperbolic discounting rate (i.e., decreasing impatience). Specifically, they tend to exhibit time inconsistent behaviors such as overconsumption and procrastination (Laibson, 1996, 1997; O'Donoghue and Rabin, 1999). Additionally, recent empirical studies revealed that individual's preferences change through exogenous shocks such as natural disasters (Callen, 2015; Cameron and Shah, 2015; Eckel et al., 2009).

I use the tsunami damage caused by the Great East Japan Earthquake in 2011 as an exogenous shock to evaluate the change in time preferences. This was the largest earthquake in Japan, with a record moment magnitude (M_W) of 9.0, causing tremendous tsunamis in addition to violent tremors. The tsunami resulted in more than 25,000 dead and missing persons. It also caused a nuclear power plant accident at the Fukushima Daiichi Nuclear Power Plant, leading to radiation contamination and planned blackouts.

I investigate whether time preferences change as a result of the damage caused by this significant earthquake as exogenous shock using the (β, δ) model of preferences, developed by Strotz (1955) and Phelps and Pollak (1968), which captures both present bias (β) and changes in discount factor (δ). The literature on time preferences stressed the importance of considering present bias, as well as the discount factor, to capture individuals' time preferences (e.g., Burks et al., 2012).

E-mail address: akesaka@iser.osaka-u.ac.jp

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Callen (2015) showed that time preference is affected by a tsunami shock. However, he only investigated the change in the discount factor. In this study, I estimate the impact of the tsunami on the discount factor, the degree of present bias, and the likelihood of being present-biased.

My findings can be summarized as follows. The time preferences of those damaged by the disaster of the tsunami have changed. The changes occurred in present bias (β) and the hyperbolic discounting dummy. The time inconsistent tendency has statistically expanded and persisted even five years since after the earthquake. However, there is no significant change in the discount factor (δ).

One key feature of this study is that I use a nationally representative panel data for analysis before and after the earthquake. Chuang and Schechter (2015) conducted a survey of the empirical studies on this topic, and pointed out that data on preferences are usually available only after a shock but not before. Especially in the case of natural disasters, researchers cannot anticipate when and where such a disaster will occur. In such cases, comparisons between those affected by the disaster and those not affected are only possible based on post-disaster surveys. However, there are differences in disaster risk by region and, thus, the distribution of individual characteristics may differ by region based on housing location. The panel data structure allows avoiding the potential bias arising from this selection problem, which is unavoidable for cross-sectional data.

My analysis contributes to the literature by investigating whether the change in time preferences caused by natural disasters is temporary or permanent. The panel data used are from the Japan Household Panel Survey on Consumer Preferences and Satisfaction (JHPS-CPS), which covers the following periods: 2011–2013, 2016, and 2017. Therefore, I can observe the changes not only immediately after the earthquake but also several years later, while previous studies have only assessed changes soon after the occurrence of a natural disaster, despite the use of panel data (Rehdanz et al., 2015; Yamamura et al., 2015). There has been no discussion on the persistence of changes in preferences except for Hanaoka et al. (2018), who found that the change in risk preferences continued even five years after a shock. To the best of my knowledge, this is the first study that investigates the long-term changes in time preferences induced by the impacts of a natural disaster.

The remainder of this study is organized as follows. Section 2 describes the data, followed by the outline of my identification strategy in Section 3. The findings are reported in Section 4. Finally, Section 5 concludes the paper.

2. Data

2.1. Data source and sample

My empirical research is based on the Japan Household Panel Survey on Consumer Preferences and Satisfaction (JHPS-CPS) conducted by the Institute of Social and Economic Research (ISER) of Osaka University during 2011–2013, 2016, and 2017. The JHPS-CPS is a nationally representative, annual panel survey of the resident population of Japan. Data are collected using self-administered paper questionnaires, which are hand-delivered to and picked up from participating households every February since 2003.[1] One feature of JHPS-CPS is that it includes a variety of behavioral economic questions related to time discounting and risk aversion, in addition to the standard household survey questions, for example, on working status and household income. A sample set was formed in 2009, with respondents for the first year to be surveyed in every subsequent year until 2013. Although the survey was suspended in 2014, it was resumed in 2016, targeting 70% of the original respondents of the 2013 survey. The last survey was carried out in 2017, targeting the previous year's respondents. I establish the study sample based on the 2,114 individual respondents in 2017, whose information is also available in the previous surveys conducted in 2011–2013 and 2016.

Since this survey is conducted every February, the survey in 2011 was conducted before the Great East Japan Earthquake (March 11, 2011). Therefore, I can observe individuals' changes both immediately after (in 2012 and 2013) and several years after the earthquake (in 2016 and 2017) using these data.

2.2. Measures of the disaster

The Great East Japan Earthquake is the largest earthquake in Japan on record so far, with a moment magnitude (M_W) of 9.0. The earthquake occurred on March 11, 2011 at 2:46 pm JST. Around 30 min later, tsunami waves, some higher than 10 m, struck along the Northeast Japan coastline. A report by the National Police Agency lists 15,854 earthquake-related deaths as of March 11, 2012, more than 90% of which were caused by the tsunami (National Police Agency, 2012). I focus on the areas engulfed by tsunamis where the damage was most severe.

As the survey does not capture information on the type of damages actually incurred, this study constructs disaster damage variables of the earthquake at municipality level based on respondents' residential information collected from the 2011 survey. The 2011 survey was conducted about a month before the Great East Japan Earthquake. Based on the sample description in Section 2.1, this study covers 144 of the total 1,718 municipalities (as of April 2016) of Japan. Figure A1 in Appendix A shows the distribution of analyzed municipalities.

An indicator variable for the tsunami takes 1 if the municipality is identified to have been submerged by the tsunami, and 0 otherwise (based on data from Saito et al., 2015). These municipalities are defined by 100 m mesh data on submerged areas

[1] All respondents were given a JPY 1,500 (USD 15) cash voucher for completing the survey.

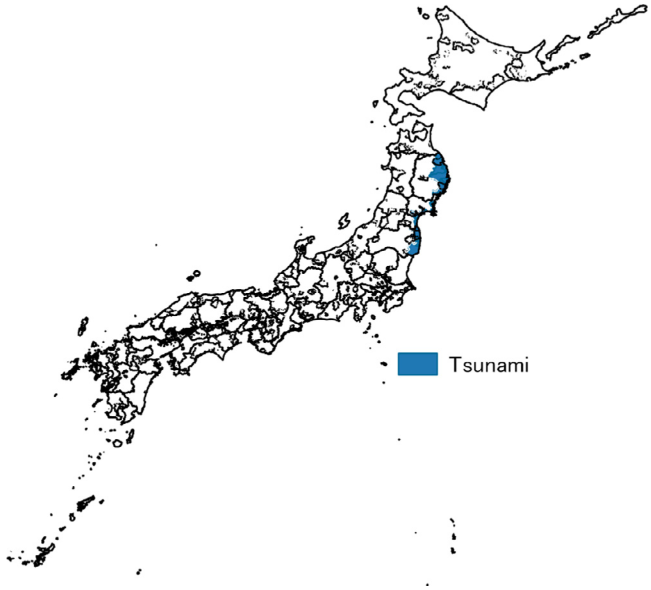

Fig. 1. Distribution of tsunami damage by the Great East Japan Earthquake.

released by the Geospatial Information Authority of Japan, constructed based on aerial photography and satellite images taken in late March 2011. The regions that suffered due to the tsunami are located along the Pacific Ocean coast across three prefectures: Fukushima, Iwate, and Miyagi. They suffered the highest number of human casualties and had the largest number of houses completely destroyed, accounting for more than 90% of the country's total damage.

Fig. 1 shows how tsunami damage is distributed in Japan.

2.3. Eliciting time preferences: quasi-hyperbolic discounting

I use responses to the JHPS-CPS intertemporal trade-off questions to calculate each individual's quasi-hyperbolic discounting parameters, decomposing time preferences into a present bias component, β, and a long-run component. δ. The JHPS-CPS for 2011–2013 and 2016–2017 contain hypothetical questions with multiple price lists, as indicated below.

Question 1:

Suppose you are to receive money from someone. You can receive money *today* or ***7** days later* from today, but the amount will be different. Compare the amounts and dates under option A and option B, and indicate which option you prefer for each of the nine combinations.

Question 2:

Suppose you are to receive money from someone. You can receive money *90* or *97 days later* from today, but the amount will be different. Compare the amounts and dates under option A and option B, and indicate which option you prefer for each of the nine combinations.

The degree of time preference is measured by the row of the multi-price list, where the respondent changes her/his choice from option A to option B (i.e., combination of prices of options A and B).[2] Between 2011 and 2012 onwards, there is a difference in the amounts quoted in the multi-price list of the questionnaire. Therefore, to compare individual time preferences in 2011 and in 2012 onwards, I rescale the values in the multi-price list and define the time discount rate only in the common cut-offs listed in Table B1.[3]

I consider a model with quasi-hyperbolic discounting (Laibson, 1997; O'Donoghue and Rabin, 1999) and exploit the two-time discounting to compute a discount factor and a present bias. A time-consistent individual should have the same (annualized) discount factor for "today or 7 days later" as "90 or 97 days later". By contrast, a present-biased individual displays decreasing impatience and has discount greater for "today or 7 days later" than "90 or 97 days later". I jointly fit an indi-

[2] Some respondents switched their choice between options A and B more than once. A total of 6.26% of respondents switched two or more times when comparing the 90 and 97 days intervals used for calculating δ. When comparing "today or 7 days later" to "90 or 97 days later" used for calculating β, 9.53% switched similarly. In Table B2, I examine the possibility of a structural correlation between the multiple switches and the damage in 2011. It shows almost no statistically significant correlations. Therefore, I drop respondents who ever switch multiple times from the analysis data. If I treat their discount factors as missing values and use other years' response, the results are basically unchanged.

[3] In Appendix F, I show that the results are robust to the alternative definitions of discount factors. See Appendix F for more details.

vidual's responses to both intertemporal questions using the quasi-hyperbolic discounting specification (1).

$$U_t = u(c_t) + \beta \sum_{\tau=1}^{T-t} \delta^{\tau} u(c_{t+\tau}), \quad \text{where } 0 \le \delta \le 1 \text{ and } 0 \le \beta \le 1. \tag{1}$$

Parameter δ (discount factor) reflects an individual's long-run patience level, while β (present bias) reflects any disproportionate weight given to the immediate present at the expense of all future periods. If $\beta = 1$, the quasi-hyperbolic discounting is the same as the traditional, time-consistent discounting, whereas $\beta < 1$ reflects a time-inconsistent present-bias. I also consider a discount function, $D(\cdot)$, such that utility u in period τ is worth $D(\tau)u$ today.

Assuming annual periods, an individual's responses to the two questions imply that

$$\begin{aligned} &Discount\ Factor\ (90\ days\ or\ 97\ days\ later) = \delta, \\ &Discount\ Factor\ (Today\ or\ 7\ days\ later) = \beta\delta. \end{aligned} \tag{2}$$

In the survey design of JHPS-CPS, the discount factor, δ, may take a value exceeding 1. Such a case is considered a corner solution, and I let δ equal 1 as δ is between 0 and 1 by definition. Similarly, when β has a value more than 1, I let β equal 1.[4] Figure B1 in Appendix B shows the distribution of β and δ in pooled observations for the entire year. For δ, 7.1% of all respondents have a time discount factor of 1. This means that the remaining 92.9% respondents consider the future value to be discounted more than the current value.

I also construct a binary indicator of hyperbolic discounting, which equals 1 if $\beta < 1$ and 0 otherwise. This indicator is more robust than β, since it does not depend on the method of determining the discounting level, but only indicates that the individual discounts more for "today or 7 days later" than for "90 or 97 days later". This indicator is also robust to any hyperbolic discounting model other than the quasi-hyperbolic one. Further, 26.3% of all respondents have a hyperbolic discounting tendency.

One potential concern about estimated time preferences stems from the validity of using hypothetical questions. In the literature, several studies have examined the coherency between hypothetical and actually incentivized time discounting decisions but did not reached consensus. For example, Coller and Williams (1999) and Kirby and Marakovi (1995) have found that individuals are more likely to be patient in hypothetical determination. Meanwhile, Johnson and Bickel (2002) and Madden et al. (2003) demonstrated no significant difference in responses between real and hypothetical time discounting decisions. Because my intertemporal discount questions are hypothetical, they might not motivate respondents to make decisions carefully to reveal their real preferences. However, in the analysis, I only need to assume that the bias is constant throughout all survey years. My empirical strategy, which considers individual fixed effects based on the panel data structure, identifies changes in preferences. Thus, the results are robust until there is a certain bias in the hypothetical questions.

Table 1 presents the summary statistics of individuals' time preferences, characteristics and damage status. In the main analysis, I control the individual fixed effects with panel data, and, thus, I do not use the variables of individual characteristics reported in this table. However, they are useful for understanding the characteristics of the sample.

Table 2 shows the t-test results, comparing the means of the time preference variables between the respondents affected and unaffected by the tsunami, based on the survey conducted before the earthquake. I find a statistically significant difference in the pre-earthquake hyperbolic discounting probability between those affected and unaffected. This indicates that if I had only analyzed data after the earthquake, I would incorrectly recognize the difference in preferences between those affected and unaffected from before the disaster as an effect of the earthquake.

3. Identification strategy

I examine the effects of the earthquake on time preferences using panel data before and after its occurrence. Employing a difference-in-difference model, I control for time-invariant individual characteristics using individual fixed effects. I capture the change in time preferences by comparing a sample of individuals affected by the earthquake (treatment group) versus those unaffected (control group). The following baseline model is used to estimate the earthquake's impact:

$$\begin{aligned} Time\ Preference_{ijt} &= \alpha_i + \beta\ Tsunami_j \\ &+ \gamma_1 Tsunami_j \times D_{2012-2013} + \gamma_2 Tsunami_j \times D_{2016-2017} \\ &+ \theta_1 D_{2012-2013} + \theta_2\ D_{2016-2017} + \varepsilon_{ijt}. \end{aligned} \tag{3}$$

where $Time\ Preference_{ijt}$ is a variable of time preferences for individual i at location j at time t and α_i represents time-invariant individual characteristics. $Tsunami_j$ is an indicator variable for tsunami damage at location j. Coefficient β on $Tsunami_j$ is not identified because the time-invariant individual fixed effects are also controlled in the model; therefore, this term is omitted from the estimation. $D_{2012-2013}$ is a dummy variable that takes the value 1 if the years are 2012 or 2013, and 0 otherwise. $D_{2016-2017}$ is a dummy variable that takes the value 1 if the years are 2016 or 2017, and 0 otherwise. The coefficients of the interactions of these dummies and $Tsunami_j$ are parameters of interest. Specifically, γ_1 represents

[4] Of the total sample, 7.67% of respondents had a discount factor (δ) greater than 1 and 13.85% a present bias (β) greater than 1. More details are included in Table B3 of the Appendix B, which presents the matrix of time discount factors of "today or 7 days later" and "90 or 97 days later." If the time discount factor for "today or 7 days later" is greater than that for "90 days or 97 days later," the value of β is greater than 1.

Table 1
Summary statistics.

Variable	Obs.	Mean (S.D.)	Min	Max
Time Preferences				
δ (Discount Factor)	9090	0.920 (0.129)	0.505	1.000
β (Present Bias)	8570	0.962 (0.096)	0.505	1.000
D[β<1](Hyperbolic Dummy)	8570	0.263 (0.440)	0	1
Damage				
Tsunami	9090	0.023 (0.150)	0	1
Individual Characteristics				
Male	9090	0.457 (0.498)	0	1
Age	9090	55.040 (12.492)	22	84
Married	9068	0.811 (0.392)	0	1
Log of annual household income	8275	2.733 (0.550)	0.732	5.113

Notes: This table reports the summary statistics of individuals. Standard deviations are reported in parentheses. The variables of individual characteristics are defined as follows: Male is a binary indicator for gender, which equals 1 if the respondent is male and 0 otherwise. Age is the respondent's age in the survey year. Married is a binary indicator for marital status that equals 1 if the respondent is married and 0 otherwise. Income denotes the log of per capita household income in million yen.

Table 2
t-test of time preferences for affected and unaffected individuals before the earthquake.

	A. Affected Mean (S.D.)	B. Unaffected Mean (S.D.)	Difference: E(A)-E(B) [S.E.]	p-Vlue H_0: E(A) = E(B)
δ (Discount Factor)	0.920 (0.136)	0.921 (0.132)	−0.001 [0.021]	0.943
β (Present Bias)	0.962 (0.106)	0.949 (0.117)	0.014 [0.018]	0.450
D[β<1](Hyperbolic Dummy)	0.167 (0.377)	0.293 (0.455)	−0.126 [0.071]	0.075

Notes: This table reports the group means of affected and unaffected individuals with corresponding deviations in parentheses. The point estimate shows the mean difference of time preferences before the earthquake between individuals who were affected and those unaffected by the tsunami with corresponding standard errors in brackets. Data are based on the survey in 2011 (before the earthquake occurred).

the changes in preferences immediately after the disaster and γ_2 the changes in preferences after a lag. θ_1 and θ_2 indicate the time effects on outcomes for each period. I do not use the year dummy variable for each year but two-period dummies after the earthquake because the number of individuals adversely affected by the tsunami is small. ε_{ijt} is the idiosyncratic random shock.

4. Results

Table 3 illustrates how the tsunami damage changes δ (discount factor), β (present bias), and the hyperbolic discounting dummy variable. Since I have two treatment variables ($Tsunami_j \times D_{2012-2013}$, $Tsunami_j \times D_{2016-2017}$), I calculate the sharpened q-values (Benjamini et al., 2006) to control for the false discovery rate (FDR), following the procedure outlined by Anderson (2008).

Column (1) shows that the tsunami does not have a statistically significant effect on the discount factor (δ). Column (2) shows the effects on the present bias (β), that is, a statistically significant negative effect of the tsunami on 2012–2013 and 2016–2017. This result implies the importance of differentiating the present bias from the discount factor. Columns (3) reports the effects on the probability of hyperbolic discounting. The tsunami significantly increases the hyperbolic probability over the period under study, and the magnitudes of the effects are reasonably large in 2012–2013 and 2016–2017. These findings suggest that time preferences are significantly affected by the tsunami after the earthquake and that the change persists in the long-term.

When I use only data after the earthquake, those who suffered from the tsunami appear to become more time-consistent after incurring damage (Table C1 in Appendix C). At least, part of the change reflects the difference in time preferences before the disaster in Table 2. This difference indicates the importance of using panel surveys before and after the earthquake.

Table 3
The effect of tsunami damage on time preferences.

Coef. [S.E.] *Adjusted p-value*	δ (Discount Factor) (1)	β (Present Bias) (2)	D[β<1](Hyperbolic Dummy) (3)
Tsunami × D[2012–2013]	0.002	−0.030	0.099
	[0.011]	[0.009]	[0.032]
	0.977	**0.029**	**0.030**
Tsunami × D[2016–2017]	0.011	−0.015	0.049
	[0.014]	[0.006]	[0.020]
	0.715	**0.084**	**0.092**
Observations	9090	8570	8570
adj. R-sq	0.000	0.009	0.002

Notes: This table reports the estimated changes in time preferences due to the tsunami. Column (1) reports the regression estimates for δ (discount factor), Column (2) the regression estimates for β (present bias), and Column (3) the regression estimates for a hyperbolic discounting dummy. All regressions include individual fixed effects, $D_{2011-2012}$and $D_{2011-2012}$. Standard errors clustered at the municipality level are reported in brackets. P-values, calculated by sharpened q-values that control the false discovery rate, are in italics and underlined.

Finally, I conduct various robustness checks involving the estimation of gender heterogeneous effects, controlling for the other damage variables, Lee (2009)'s bounds for selective attrition, changes in the empirical model specification, and changes in the variable definitions and the analysis sample. The main results on the present bias parameter (β) and hyperbolic discounting dummy are robust to these additional analyses.[5]

5. Conclusion

I investigate whether individuals' time preferences are changed by the damage caused by the tsunami due to the Great East Japan Earthquake of 2011 using panel surveys before and after the earthquake. I find that the change in the time discount factor (δ) is not statistically significant for those who are adversely impacted by the tsunami, although the present bias tendency is significantly increased (shrinking β). The hyperbolic discounting dummy also shows an increase in time inconsistency.

The findings suggest that the changes in present bias tendency for those affected by a disaster are an important factor in the post-disaster reconstruction process, and might partly explain the differences between immediate and delayed reconstruction performances following disasters worldwide. The psychology literature points out that there exists a relationship between stress and delay discounting (Fields et al., 2014). However, due to data limitations, I am unable to clarify in detail why and how time preferences were affected by the disaster. These questions are beyond the scope of my study and are thus left for future research.

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Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jebo.2019.08.013.

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[5] See Appendix D, E and F for a more detailed explanation of the robustness check.

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