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Time Preferences in the Gain and Loss Domains: An Incentivized Experiment

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Abstract

Present-biased preferences in intertemporal decisions have been actively investigated. While these preferences have been elicited through incentivized experiments in the gain domain to avoid potential hypothetical bias, they have been elicited only through hypothetical experiments in the loss domain. We conducted a two-stage experiment that enabled us to elicit these preferences in the gain and loss domains in an incentive-compatible way. We found that present bias, which is exhibited in both domains, is more severe in the loss domain.

Keywords: Intertemporal choice, Present bias, Gains and losses

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Highlights

- We conducted a two-stage experiment that enabled us to elicit time preferences in the gain and loss domains in an incentive-compatible way.
- We found that present bias in both domains.
- We found that the degree of present bias was significantly more severe in the loss domain than in the gain domain.

1. Introduction

Many of our important decisions involve a time component, and these decisions often involve gains and losses. Individual time preferences, in particular present-biased preferences, have been investigated for decades (Abdellaoui et al., 2013; Andersen et al., 2008; Andreoni & Sprenger, 2012; Benhabib et al., 2010; Frederick et al., 2002; Laibson, 1997; Loewenstein & Thaler, 1989; Thaler, 1981).

A person with present-biased preferences overvalues present outcomes or undervalues future outcomes. Such a preference leads to time-inconsistent behaviors. For example, a person with present-biased preference planning to save €200 in 30 days would end up saving less than €200 when the future comes because shopping or other options at the time become more attractive than the person expected. This planning failure would cause insufficient savings (Laibson, 1997). Using the same reasoning, present bias could explain many serious problems in our life such as credit card debt (Meier & Sprenger, 2010), excessive body mass index (BMI) (Courtemanche et al., 2015), and smoking addiction (Ida, 2014).

Are people's time preferences similar in decisions involving gains and in decisions involving losses? Some researchers, such as Benzion et al. (1989), MacKeigan et al. (1993), and Thaler (1981), have argued they are not. These papers compared the estimates of individual discount rates (IDRs) in the gain and loss domains.[1] Some previous experiments reported the sign effect, in which IDRs are higher in the gain domain than the loss domain (Thaler, 1981; for a review, see Frederick et al., 2002). However, Shelley (1993) did not find the sign effect, and the opposite of the sign effect has been found by merely changing the frames of the intertemporal decisions, e.g., an acceleration frame in which the default is to realize the outcomes in the future and a delayed frame in which the default is to realize the outcomes today (Appelt et al., 2011; Benzion et al., 1989; Shelley, 1993, 1994).

Disagreements about the differences between the gain and loss domain also exist in the literature on the magnitude of the present bias. Thaler (1981) found that discount rates dropped sharply as the timing of the future outcomes was delayed in the gain domain, which is consistent with present-biased preferences, but this pattern was not found in the loss domain. However, Abdellaoui et al. (2013) and Shiba and Shimizu (2020) showed that the majority of participants in their experiments were present-biased in the gain and loss domains. While Abdellaoui et al. (2013) found that the level of present bias in the loss domain was higher than in the gain domain, Shiba and Shimizu (2020) could not find a difference between the two domains in most cases. An important characteristic of all these previous studies investigating the present bias in the loss domain is that they used hypothetical decisions. Thus, they potentially suffer from hypothetical bias (see Frederick et al., 2002).

There have been debates about whether using hypothetical scenarios instead of conducting an incentive-compatible experiment affects time preferences in the gain domain. Frederick et al. (2002) argued that it is uncertain whether with hypothetical rewards people are motivated to, or capable of, accurately predicting what they would do if outcomes were real. Another paper found that IDRs were lower for hypothetical rewards (Kirby & Maraković, 1995), although other studies observed no difference in discount rate with real and hypothetical rewards (Johnson & Bickel, 2002; Madden et al., 2003). There have been similar extensive debates in risk preferences in both domains. Camerer and Hogarth (1999) reviewed 13 papers on risk preferences and reported that when incentivized, individuals became more risk averse in 8 papers, became more risk seeking in 2 papers, and did not change their risk preferences in 3 papers.

Other studies found that offering incentives increased risk aversion in lottery choice questions (Holt & Laury, 2002, 2005). Furthermore, Weber et al. (2004) showed that individuals became more risk averse for gains and less risk seeking for losses in incentive-compatible conditions. Importantly, the effects were stronger in the loss domain. This implies that the extent of the hypothetical bias is different in the gain and loss domains. Construal-level theory (Trope & Liberman, 2010) claims that both time (delay) and probability (risk) are perceived as introducing psychological distance. Thus, it is reasonable to assume that experiments on time preferences may also suffer from hypothetical bias and that the extent of the bias is different in the gain and loss domains as well. In this paper, we elicit time preferences both in the gain and loss domains in an incentive-compatible manner to fill this gap in the literature.

Incentivizing choices that involve losses in experiments is challenging because it is generally difficult for experimenters to take money away from the participants (Frederick et al., 2002). Thus, in experiments involving losses, participants are typically given an initial endowment that is enough to cover the maximum possible loss (Tom et al., 2007). This method has been also used to measure IDRs (Xu et al., 2009; Zhang et al., 2016) and loss aversion (Kirchler et al., 2018).[2] However, providing an endowment to participants could also introduce an unwanted bias in the experiment known as the house-money effect (Thaler & Johnson, 1990). That is, individual behaviors may be affected (e.g., display more risk-loving behaviors) when prior windfall gains are given. The house-money effect can be avoided by making participants earn money through unrelated tasks before the main part of an experiment (Bosch-Domènech & Silvestre, 2010). The present study applies this two-stage method.

Our two-stage experiment enables an unbiased incentivization of time preference elicitation in the loss domain. In the first stage, the participants took a part of a nonverbal IQ test (the advanced version of Raven's Progressive Matrices Test, Raven, 2003) and earned an amount of money that was enough to cover the maximum possible loss in the second stage. Two weeks after the first stage, time preferences in the gain and loss domains were elicited. Using Raven's test in the first stage also allows us to analyze the relationship between cognitive skills and present bias, as well as impatience (IDRs), in both domains.[3]

The results from our incentivized experiment consistently show that time preferences in the gain and loss domains are different. A descriptive analysis shows that immediate future losses are more heavily discounted than immediate future gain, while both are only mildly discounted in the further future. It appears that, therefore, the present bias is more severe in the loss domain. Further investigation through regression analyses reveals that there is a significant level of present bias in both domains and that the present bias is indeed more severe in the loss domain. These results are in line with Abdellaoui et al. (2013).

Our results imply that one should be careful about using the degree of present bias estimated in the gain domain to design a policy to intervene in time-inconsistent behaviors involving losses. Furthermore, we found that participants with higher cognitive skills tend to be more patient and less present-biased in both the gain and loss domains.

2. Method

2.1 Participants

We recruited 80 students from ESC Dijon Bourgogne who agreed to participate in the entire experiment, including the first stage conducted on February 19th and 20th and the second stage conducted on March 2nd and 3rd on campus in 2015. There were three sessions in the experiment. In total, 68 participants (73.5% female, M_{age} = 22.3 years, age range: 20–29 years) completed both stages of the experiment. On average, the experiment took approximately 65 minutes in total (20 minutes in the first stage and 45 minutes in the second stage). The participants received €19.23 in total (€17.79 in the first stage and €1.44 in the second stage). The total payments were positive for all participants.

2.2 Design and procedure

The entire experiment was computerized and implemented by z-tree (Fischbacher, 2007). The subjects were told that there were two stages in the experiment and that they might lose money in the second stage. They were also told that the possible maximum loss was the same as the minimum gain in the first stage, so they would not lose money in total, and there was a high possibility that they could earn a substantial amount of money.

The first stage was the earning stage. The participants took the nonverbal IQ test and earned either €20 or €15 depending on whether their scores were above the average score of the participants in the same session or not (38 participants received €20 and 30 participants received €15). The same participants came back to the lab after two weeks and brought at least €15 with them. In the second stage, they made two sets (gains and losses) of intertemporal decisions followed by demographic questions.[4] Half of the participants made decisions in the gain domain first while the other half started with the loss domain.

Our intertemporal decision tasks were based on Tanaka et al. (2010), who used the multiple price list (MPL) method, which provides a list of choices between two options: a sooner but smaller outcome and a later but larger outcome. The drawback of the MPL method is that only ranges of IDRs can be estimated. To estimate the exact values of IDRs (Benhabib et al., 2010; Manzini & Mariotti, 2014), we employed matching tasks incentivized by the Becker–DeGroot–Marschak (BDM) (Becker et al., 1964) mechanism (to be described in detail in the Incentive system subsection below). With this method, the IDRs can be estimated by asking today's equivalent value of a certain outcome in the future. Specifically, in the gain domain, the participants were asked to declare the minimum amount of money that they preferred to receive today instead of receiving Y euros in t days. Similarly, in the loss domain, the participants were asked to declare the maximum amount of money that they preferred to lose today instead of losing Y euros in t days. The declared values cannot exceed Y euros as in Tanaka et al. (2010). Four values of Y (3, 6, 10, 15) and five values of t (3, 7, 14, 21, 28) were used, so there were 20 intertemporal decisions to make for each domain. [5] Figure 1 shows a screen-shot of the decision screen used in the experiment.

Insert Figure 1 about here.

2.3 Incentive system

At the end of the experiment, one question was randomly chosen from each domain, and then a computer generated a random number for each of the chosen questions to determine the outcomes. In the gain domain, if a participant's declared value was *smaller or equal* to the random number, the participant received "today" an amount of money equal to the number drawn. Otherwise, the participant received Y euros in t days, as specified in the chosen question. Similarly, in the loss domain, if the declared value was *larger or equal* to the random number, the participant lost an amount of money equal to the number drawn today. Otherwise, the participant lost Y euros in t days, as specified in the chosen question. In both domains, the dominant strategy for the participant is to declare the amount that makes the participant indifferent between gaining or losing such an amount today and the Y euros with the delay of t days. The participants were told so in the instructions for each set.

To facilitate the participants' understanding of the BDM mechanism, we supplemented our instructions with a figure (see online Appendix). The instructions were computerized and read aloud by a computer-generated voice. To check participants were paying attention to the instructions, in the middle of the instructions, one number was shown (but they cannot come back to check this number), and the participants were asked to enter it in order to proceed to the next page. All the participants entered the correct numbers.

At the end of the experiment, the participants received a document stating the amount of money they would receive and pay on specific dates. They had to go to the school's administration office to collect their payments, thus the transaction costs (which were anyway very small for them because most of them came to the campus every weekday) were the same for both domains. Only four participants, whose gain and loss were the same amount to be realized on the same day, did not show up for the payments.

2.4 Models

For our parametric analysis to estimate time preferences, we employ the quasi-hyperbolic discount function βe^{-rt} (when $t > 0$ and 1 otherwise) (Laibson, 1997). A number of experimental studies (Loewenstein & Thaler, 1989; Tanaka et al., 2010) have estimated the level of present bias with this function. Under this formulation, between any two future periods, later values are discounted by a constant rate r. r describes the level of long-term impatience, and we call it the conventional discount rate. Between *today* and any future point, however, in addition to discounting by the conventional discount rate r, future values are discounted even further as represented by the multiplicative term β (that represents the degree of present bias). This function captures typical behaviors of disproportionately discounting immediate future outcomes (i.e., overvaluing today's outcomes) (Laibson, 1997). The quasi-hyperbolic discount function implies that people become more impatient only for immediate outcomes, otherwise their level of patience is the same across time.

3. Results and Discussion

Figure 2 shows a ratio of the participants' declared values *X* to the future values given in intertemporal questions *Y* across time *t*. This represents how heavily the participants discount delayed outcomes at time *t*. For example, the median values of the figure show that the future gains in 21 days are approximately 70% of their values today whereas the future losses in 21 days become approximately 50% of their values today. For each delay *t*, the median values of the ratio in the loss domain are lower than those in the gain domain, that is, the future losses are discounted more than the future gains. Furthermore, in both domains, while the shortest delayed outcomes (t = 3) are drastically discounted, further delays are discounted at an almost constant rate. These patterns are consistent with the quasi-hyperbolic discounting function. In fact, the IDRs from $t = 3$ further toward the future do not deviate from a constant (repeated measures ANOVA: $F(3, 67) = 0.237$, $p > 0.1$).

Insert Figure 2 about here.

3.1 Parameter estimates

To further analyze the time preferences in the gain and loss domains, we conduct a set of regression analyses based on the quasi-hyperbolic discounting model.[6] Assuming the linear utility function ($U(X) = X$), the present value (X) of a certain future value (Y) with delay t declared by the participants can be expressed as $X = Y\beta e^{-rt}$ (results relaxing the linear utility assumption as well as allowing for a degree of loss aversion are shown in Appendix). This equation can be easily linearized to estimate the time preference parameters:

$$ln\left(\frac{X}{Y}\right) = ln(\beta) - t \cdot r \qquad (1)$$

We estimate the present bias β and the conventional discount rate r using OLS with clustered standard errors (at the individual level). Columns (1) and (2) of Table 1 show that β is significantly different from 1 in both gain (Column (1)) and loss (Column (2)) domains, suggesting that participants' preferences are present-biased on average. The present bias in the gain domain β^{+} is less severe than in the loss domain β^{-}, and the conventional discount rates in the gain domain r^{+} are higher than the discount rates in the loss domain r^{-}.[7]

To test whether these estimated values of parameters statistically differ between the two domains, we add a dummy variable called Loss (which takes the value one if questions are from the loss domain, and zero otherwise) to the equation (1) above to obtain:

$$ln\left(\frac{X}{Y}\right) = ln(\beta) + \theta_1 \cdot Loss - t(r + \theta_2 \cdot Loss) \quad (2)$$

Column (3) of Table 1 reports the result of this regression. It shows that the estimated coefficient of Loss (θ_1) is significantly different from 0, indicating that the degree of present bias is indeed different in the gain and loss domains, while the estimate of θ_2 is not significantly different from 0, suggesting that the conventional discount rates are not different in the two domains. This pattern of higher values of β and r in the gain domain than in the loss domain is in line with Abdellaoui et al. (2013), although the absolute values of the estimated parameters are different (Table 2).

Insert Table 1 about here.

Insert Table 2 about here.

3.2 Individual level analysis

On average, we found that the present bias in the loss domain is more severe than in the gain domain. In this section, we conduct analyses for each individual. This is meaningful given the large degree of heterogeneity suggested by the wide inter-quantile ranges of the boxplots shown in Figure 2. First, we estimate each participant's conventional discount rate and present bias based on the quasi-hyperbolic discounting model. Figure 3 shows the histograms of the estimated values of participants' present bias $\hat{\beta}$ and conventional discount rate $\hat{r}$ in both domains. $\hat{\beta}^{+}$ is less than 1 for 92.6% of participants and $\hat{\beta}^{-}$ is less than 1 for 98.5% of participants. Both $\hat{\beta}^{+}$ and $\hat{\beta}^{-}$ are significantly different from 1 (Sign test: $p < .01$; Sign test: $p < .01$), and $\hat{\beta}^{-}$ is significantly lower than $\hat{\beta}^{+}$ (Sign test: $p < .01$). For the conventional discount rates, $\hat{r}^{+}$ and $\hat{r}^{-}$are significantly different from 0 (Sign test: $p < .01$; Sign test: $p < .01$), but they are not different from each other (Sign test: $p > .1$). As Figure 4 shows, we found a weak positive correlation between $\hat{\beta}^{+}$ and $\hat{\beta}^{-}$ ($r(66) = .25$) and a weak positive correlation between $\hat{r}^{+}$ and $\hat{r}^{-}$ ($r(66) = .25$). This degree of correlation of the present bias between the two domains is weaker than what Shiba and Shimizu (2020) reported.

Insert Figure 3 about here.

Insert Figure 4 about here.

We also examine whether cognitive skills are correlated with the time preference variables (IDRs, present bias, and conventional discount rates). First, we regress IDRs in both domains on the score of Raven's test (IQ score). To control for the income effect, we add the dummy variable Earnings, which takes the value 1 and 0 if a participant received €20 and €15 in 1st stage, respectively. Table 3 shows that the IQ score has a significant negative effect on IDRs in both domains (i.e., cognitive skills are positively correlated with patience). This finding is consistent with previous studies (Dohmen et al., 2010; Frederick, 2005). Table 4 also shows that the IQ score has a significant negative effect on $\hat{\beta}^{-}$ and a marginally significant negative effect on $\hat{\beta}^{+}$ but not on $\hat{r}$, indicating that the IQ score is correlated only with the present bias but not with conventional discount rates, especially in the loss domain.[8] Finally, we examine the correlation of the time preferences variables with self-reported behavioral variables which potentially relate to impatience, i.e., the amount of tobacco and alcohol consumption and the amount of money spent on leisure. However, none of them displays even mild correlations ($\rho < 0.2$).

Insert Table 3 about here.

Insert Table 4 about here.

4. General Discussion and Conclusions

Our two-stage design enabled us to conduct an incentivized experiment on time preferences in the loss domain. With multifaceted approaches, we found significant differences in time preferences in the gain and loss domains. First, in both domains, our boxplot shows substantial discounting of the outcomes with a short delay, and then discounting at approximately constant rates for future outcomes with further delays. The shortest delayed outcomes were discounted more in the loss domain. These patterns suggest that a more severe present bias is exhibited in this domain. Second, we performed a regression analysis with the quasi-hyperbolic discounting model. This model was chosen because statistical analysis showed that the IDRs did not deviate from a constant after the shortest delay. It showed that present bias existed in both domains, and it was more severe in the loss domain than in the gain domain on average. This pattern is consistent with Abdellaoui et al. (2013). The individual-level analysis also indicated that participants exhibited a more severe present bias in the loss domain than in the gain domain. Furthermore, the IQ test score was negatively correlated with IDRs and the level of present bias in both domains. In other words, the participants with higher cognitive skills were more patient and demonstrate a lesser degree of present bias on average.

Our study employed a matching-task elicitation method rather than the choice-task elicitation via MPLs to estimate IDRs. Both choice tasks and matching tasks were frequently used in previous experiments on time preferences. We chose matching tasks because the exact values of IDRs can be estimated with them whereas only the range of IDRs can be estimated with choice tasks. Another reason is that matching tasks allow us to avoid the ordering of choice set in the MPL influencing the stated preferences, i.e., the anchoring effect (Frederick et al., 2002). That is, when people make decisions between immediate and delayed rewards, the first choice they face often influences subsequent choices in choice tasks while the matching-task elicitation does not have this problem.[9] However, some studies of risk preferences argue that, due to the differences in the complexity of the task, matching-task elicitation can bias the estimations more than choice tasks (Bostic et al., 1990). Furthermore, a preference reversal occurs when the ranking of two (or more) items depends on the method used to elicit it (Lichtenstein & Slovic, 1971; Lindman, 1971). To see if our estimations are affected by the specific elicitation method, we compared our results with Tanaka et al. (2010), who used the same methods as ours except that they employed MPL for their elicitation. The parameters estimated by Tanaka et al. (2010) were fairly close to ours, suggesting that our data are reliable (Table 2).

The IDRs are larger in the loss domain in our data. In other words, the future losses are discounted more than the future gains. These results are the opposite of Thaler (1981), but in line with Appelt et al. (2011), Benzion et al. (1989), and Shelley (1993). This may have been caused by the direction effect (Appelt et al., 2011; Read, 2004), which claims that IDRs differ depending on how intertemporal decisions are framed. Specifically, intertemporal decisions can be presented using an acceleration frame (when the default is to realize the outcomes in the future) or using a delayed frame (when the default is to realize the outcomes today). Our intertemporal decisions use an acceleration frame because we asked participants to specify the present values of certain future outcomes. While Appelt et al. (2011), Benzion et al. (1989), and Shelley (1993) employed an acceleration frame as we did, Thaler (1981) used a delayed frame.

Our findings have potentially important policy implications. Many interventions for present-biased and time-inconsistent people have been discussed to help them improve their intertemporal decisions (Bryan et al., 2010; Hershfield et al., 2011; Milkman et al., 2013; Thaler & Benartzi, 2004). The higher level of present bias in the loss domain implies that a stronger degree of intervention in the loss domain is preferable. Therefore, practitioners should be careful to intervene on present-biased people when decisions involve losses (e.g., paying credit card debts and making payments by installments).

In addition, it is widely known that even when providing logically equivalent information to individuals, merely changing the framing of questions affects preferences and behaviors (Kühberger, 1998; Levin et al., 1998; Tversky & Kahneman, 1981). This framing effect is also a possible effective nudge to help improve individual behaviors (Thaler & Sunstein, 2008). Less severe present bias in the gain domain than in the loss domain implies that presenting choices as a gain frame instead of as a loss frame can potentially mitigate time-inconsistent behaviors in important intertemporal decisions. For example, for obese people to reduce their food intake, a policymaker may want to present a recommended meal plan in a gain frame (e.g., you can have 2,500 calories today) instead of presenting the meal plan in a loss frame (e.g., you need to reduce 500 calories today).

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Appendix

Estimation with a Constant Relative Risk Aversion Utility Function

Many experimental studies (not only with regards to time preferences) assume a linear utility function when small payments are involved, as we did in our analyses. We nevertheless should consider nonlinear utility functions because this could affect our estimations of present bias and conventional discount rates. Therefore, we repeat our regression analysis to estimate the parameters allowing for constant relative risk aversion preferences.

The sign-dependent utility function is defined in the gain domain by $U(x) = x^{\zeta^+}$ and the loss domain by $U(x) = -\lambda(-x)^{\zeta^-}$ (c.f., Abdellaoui et al., 2007). The parameter λ indicates the level of loss aversion. For gains (losses), the power function is concave (convex) if the value of ζ is less than 1, linear if the value is equal to 1 and convex (concave) if ζ is more than 1. With this utility function, the model to be estimated becomes:

$$ln\left(\frac{X}{Y}\right) = \frac{1}{\zeta}(ln(\beta) - t \cdot r) \quad \text{(A1)}$$

Our approach is to estimate β and *r* assuming various values of ζ because all three parameters cannot be simultaneously estimated in Equation (A1).[10] Figure A1 summarizes the results, and it shows that our findings are mostly robust to different values of ζ. For example, Table A1 shows the results when we use the estimated values of the parameters from Abdellaoui et al. (2007) ($\zeta^+ = 0.576$ and $\zeta^- = 0.567$).[11] The present bias is significantly different from 1 although it is closer to 1 compared to the estimates under the linear utility assumption. The difference of β in the two domains is still highly significant, and the value of *r* is not statistically different.

As one can see in equation (A1), the loss aversion parameter λ is canceled out in the intertemporal decisions in the loss domain, thus our results are independent of the degree of loss aversion. This specification of loss aversion has been commonly used in the previous literature (Bleichrodt et al., 2001; Booij & van de Kuilen, 2009; Fishburn & Kochenberger, 1979; Tversky & Kahneman, 1992). However, this independence from loss aversion is no longer true in other specifications. For example, if loss aversion is time-dependent (i.e., the level of loss aversion changes as the timing of outcomes is delayed). This is beyond the scope of the paper, but future research could investigate whether loss aversion is time-dependent or not.

Footnotes

1. The IDRs are commonly used to measure impatience and describe how heavily an individual discounts future outcomes regarding money, goods, health, the environment, etc. For example, if the individual is indifferent between receiving €105 in a year and receiving €100 today, their yearly IDR is 5%.

2. Xu et al. (2009) and Zhang et al. (2016) found the sign effect but they did not measure the present bias.

3. Some previous papers found that cognitive skills are positively correlated with patience (i.e., low IDRs) (Benjamin et al., 2013; Burks et al., 2009; Dohmen et al., 2010; Oechssler et al., 2009; see Shamosh & Gray, 2008 for earlier studies). Among them, Benjamin et al. (2013) and Burks et al. (2009) investigated the relationship between cognitive skills and present bias in the gain domain and showed that higher cognitive skills were associated with a lower level of present bias. However, to the best of our knowledge, the relationship between cognitive skills and present bias in the loss domain has not yet been explored.

4. The demographics include age, gender, height, father's highest degree, mother's highest degree, the city they are from, the number of siblings, the number of packs of cigarettes they smoke per week, the amount of alcohol they take per week, the amount of money they spend per month, the amount of money for leisure they spend per month and their mother tongue.

5. One practice question for each domain was provided right before the main questions for the participants to understand what intertemporal questions actually look.

6. Our analysis is based on the quasi-hyperbolic discount function, but we also considered two other common discount functions to estimate participants' time preferences: the exponential discount function (Samuelson, 1937) and the general hyperbolic discount function

(Loewenstein & Prelec, 1992). We compared the goodness of fit of the three models. Nevertheless, the quasi-hyperbolic discount function appears to be the best. According to a nonlinear regression analysis, the quasi-hyperbolic discount function gives the highest adjusted R^2 in both domains. More details of these analyses are available from the authors on request.

7. We found that the declared values were the maximum values (Y) on few observations (about 9%). Nevertheless, these observations potentially include censored declared values if the participants negatively discount the future values. Thus, we repeated the regression analysis after eliminating these observations for our robustness check. The overall findings did not change. Present bias in both domains and more severe present bias in the loss domain were found. More details of these analyses are available from the authors on request.

8. In the regressions, we use the dependent variables estimated from the quasi-hyperbolic discount function, so the results might suffer from heteroscedasticity. Therefore, we repeated the regression analysis using feasible generalized least square (FGLS). Nonetheless, the results of the two models are fairly close. More details of these analyses are available from the authors on request.

9. For example, people would be more likely to choose $60 in 1 month over $50 today if they first chose between $50 today and $51 in 1 month than if they first chose between $50 today and $70 in 1 month.

10. The number of unknown parameters (β, r, ζ) is larger than the number of known variables from our experiment (*X/Y*, *t*) in Equation 3. Therefore, the equation has infinite combinations of the three parameters that minimize its econometric model’s error term.

11. We believe these values are much lower than would be applicable to our experiment because they used very large payments in their experiment (more than 40,000 French francs: approximately €5200).

Table 1

Regression Analysis with Quasi-hyperbolic Discounting Model

	(1) Gain	(2) Loss	(3) All
β [= *exp(constant)*]	0.634***	0.432***	
	(0.0348)	(0.0343)	
r [= *time* * (−1)]	0.00950***	0.00715**	
	(0.00315)	(0.00334)	
Constant	−0.455***	−0.839***	−0.455***
	(0.0548)	(0.0794)	(0.0548)
t	−0.00950***	−0.00715**	−0.00950***
	(0.00315)	(0.00334)	(0.00315)
Loss			−0.384***
			(0.0869)
t * Loss			0.00235
			(0.00399)
N	1360	1360	2720
adj. R^2	0.014	0.004	0.049

Notes: Clustered standard errors in parentheses; *, **, and *** stand for statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2

Comparison with Previous Papers Using Quasi-hyperbolic Discounting Function

	Tanaka et al. (2010)	Abdellaoui et al. (2013)	Benhabib (2010)[*1]	This study
N	178	65	27	68
Elicitation	MPL	MPL	BDM	BDM
Highest outcome	300,000 dong	€500	$100	€15
Longest delay	3 months	3 years	6 months	1 month
Incentivized	Yes	No[*2]	Yes	Yes
$\hat{\beta}^{+}$	0.644	0.94	0.979	0.634
$\hat{r}^{+}$	0.008	0.000301	-	0.0095
$\hat{\beta}^{-}$	-	0.91	-	0.432
$\hat{r}^{-}$	-	0.000137	-	0.00715

[*1]The estimated parameters are calculated from the average of individual parameters.

[*2]Incentivized experiment was conducted only in the gain domain.

Table 3

Regression Analysis of Daily Individual Discount Rates

	(1) Gain	(2) Gain	(3) Loss	(4) Loss
IQ_score	−0.0140***	−0.0121**	−0.0208**	−0.0224**
	(0.00526)	(0.00535)	(0.00927)	(0.00956)
Earnings	0.00931*	0.00888	0.0158	0.0167*
	(0.00545)	(0.00544)	(0.00959)	(0.00973)
Age		−0.000575		−0.00399
		(0.00452)		(0.00808)
Female		0.0318*		−0.0265
		(0.0186)		(0.0333)
Cons	0.0564	0.0334	0.0719	0.181
	(0.0620)	(0.111)	(0.109)	(0.197)
N	68	68	68	68
adj. R^2	0.078	0.091	0.044	0.029

Notes: The dependent variable is the daily individual discount rate. Standard errors in parentheses; *, **, and *** stand for statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4

Linear Regression Analysis of the Estimated Beta $\hat{\beta}$ and Conventional Discount Rate $\hat{r}$

	(1) $\hat{\beta}^{+}$	(2) $\hat{\beta}^{-}$	(3) $\hat{r}^{+}$	(4) $\hat{r}^{-}$
IQ_score	0.0376*	0.0525***	−0.00268	−0.00146
	(0.0196)	(0.0191)	(0.00210)	(0.00233)
Earnings	−0.0168	−0.0441**	0.00478**	0.000871
	(0.0200)	(0.0195)	(0.00214)	(0.00237)
Age	0.00528	0.00657	0.000913	−0.00120
	(0.0166)	(0.0162)	(0.00177)	(0.00197)
Female	−0.0939	−0.0609	0.00651	−0.00166
	(0.0684)	(0.0666)	(0.00730)	(0.00811)
Cons	0.549	0.643	−0.0728*	0.0349
	(0.406)	(0.395)	(0.0434)	(0.0481)
N	68	68	68	68
adj. R^2	0.077	0.082	0.045	−0.049

Notes: Standard errors in parentheses; *, **, and *** stand for statistical significance at the 10%, 5%, and 1% levels, respectively.

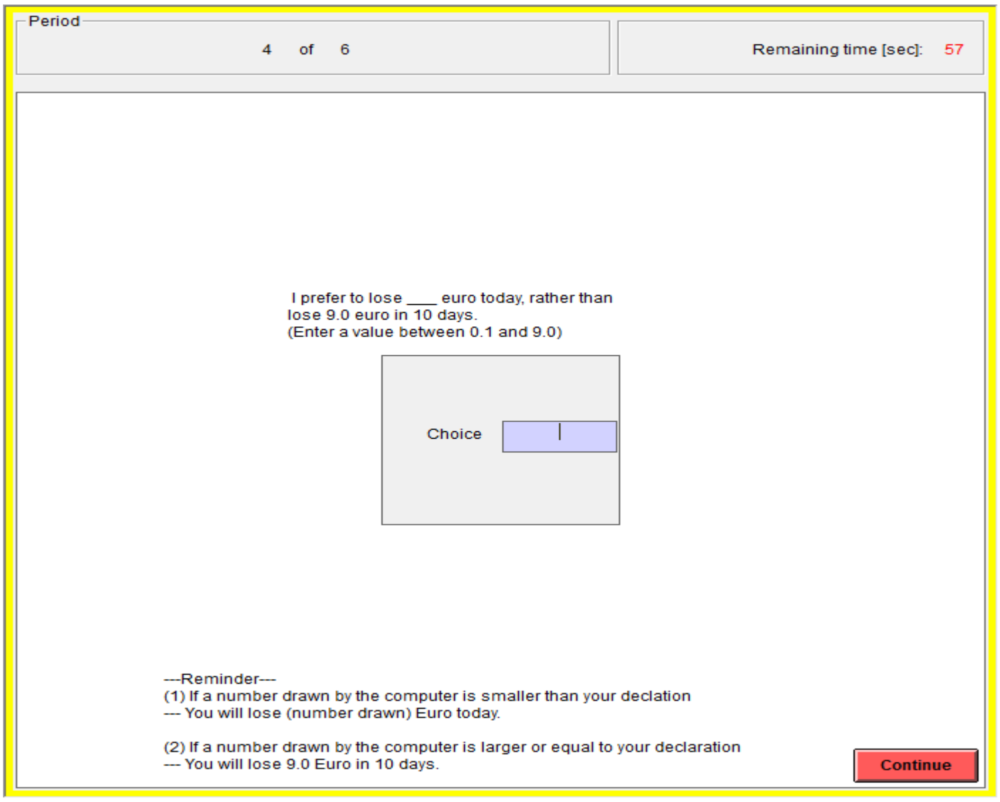

Figure 1. Screenshot of one of the Questions in the Experiment.

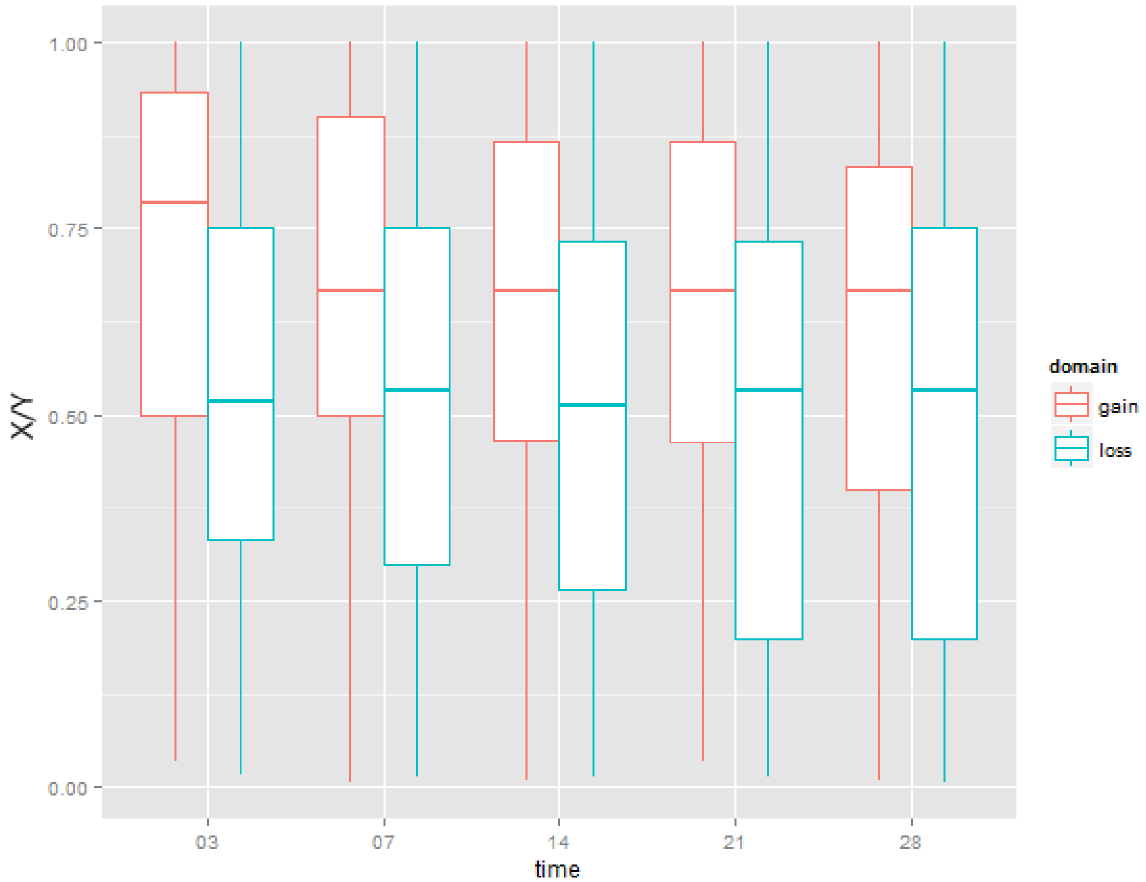

Figure 2. Ratio of Declared Present Values X to Future Outcome Y across Delay Scenarios. The horizontal line inside each box is the median, and the bottom and top of the box are the first and third quartiles, respectively.

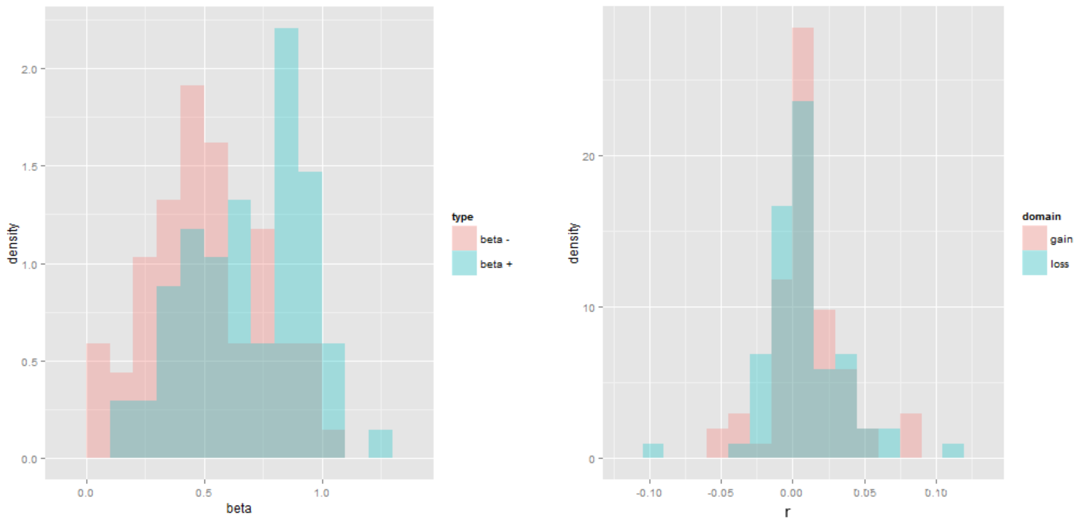

Figure 3. Distribution of Estimated Present Bias and Conventional Discount Rates in Gain and Loss Domains.

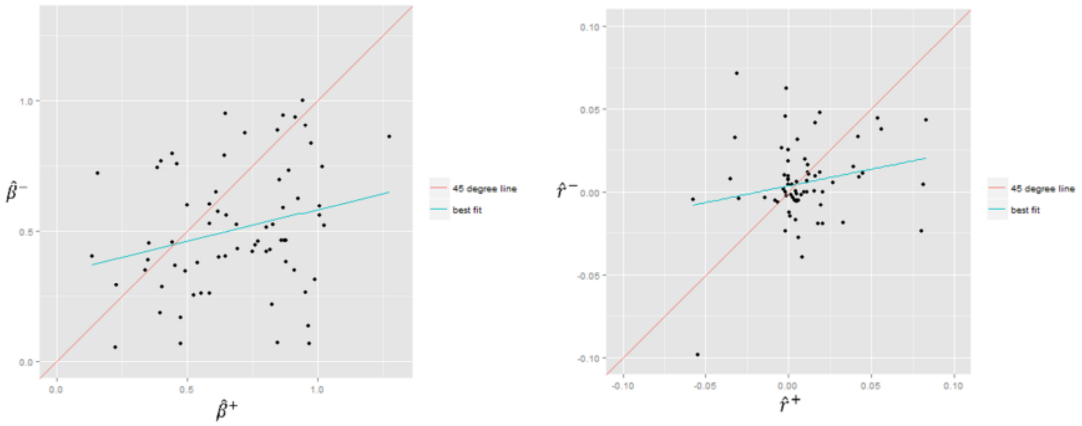

Figure 4. Scatterplot of Estimated Present Bias and Conventional Discount Rates in Gain and Loss Domains.

Appendix

Table A1

Regression Analysis with Quasi-hyperbolic Discounting Model Assuming CRRA Utility Function

	(1) Gain	(2) Loss	(3) All
β [= *exp(constant)*]	0.769***	0.621***	
	(0.0243)	(0.0280)	
r [= *time* * (−1)]	0.00547***	0.00405**	
	(0.00182)	(0.00189)	
Constant	−0.262***	−0.476***	−0.262***
	(0.0316)	(0.0450)	(0.0316)
t	−0.00547***	−0.00405**	−0.00547***
	(0.00182)	(0.00189)	(0.00182)
Loss			−0.214***
			(0.0495)
t * Loss			0.00142
			(0.00228)
N	1360	1360	2720
adj. R^2	0.014	0.004	0.049

Notes: Clustered standard errors in parentheses; *, **, and *** stand for statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure A1. The Values of β and r in the Gain and Loss Domains with Different Utility Curvature ζ.