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Comparing mixed intertemporal tradeoffs with pure gains or pure losses

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Abstract

Intertemporal choices involve tradeoffs between outcomes that occur at different times. Most of the research has used pure gains tasks and the discount rates yielding from those tasks to explain and predict real-world behaviors and consequences. However, real decisions are often more complex and involve mixed outcomes (e.g., sooner-gain and later-loss or sooner-loss and later-gain). No study has used mixed gain-loss intertemporal tradeoff tasks to explain and predict real-world behaviors and consequences, and studies involving such tasks are also scarce. Considering that tasks involving a combination of gains and losses may yield different discount rates and that existing pure gains tasks do not explain or predict real-world outcomes well, this study conducted two experiments to compare the discount rates of mixed gain-loss intertemporal tradeoffs with those of pure gains or pure losses (Experiment 1) and to examine whether these tasks predicted different real-world behaviors and consequences (Experiment 2). Experiment 1 suggests that the discount rate ordering of the four tasks was, from highest to lowest, pure gains, sooner-loss and later-gain, pure losses, and sooner-gain and later-loss. Experiment 2 indicates that the evidence supporting the claim that the discount rates of the four tasks were related to different real-world behaviors and consequences was insufficient.

Keywords: intertemporal choice, mixed outcome, discount rate, real-world behavior, real-world consequence

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1 Introduction

In daily life, many decisions involve tradeoffs between outcomes that occur at different times, such as spending money or saving it by placing it in a retirement account. Such tradeoffs are referred to as "intertemporal choices" (Frederick et al., 2002). How we would like to experience intertemporal outcomes is central to our well-being. Most laboratory studies on intertemporal choices involve participants making choices between pairs of positive dated outcomes that usually involve money—one smaller-but-sooner and the other larger-but-later, such as receiving $200 now or $300 in six months.

However, such receiving tasks can represent only purely profitable real-world situations, such as buying a new mobile phone with a bonus or putting the bonus into a retirement account for later use (i.e., pure gains). In fact, many decisions involve costs, even combinations of costs and benefits. For example, an individual may choose to suffer a potentially painful dental treatment now or choose to go to the dentist later but suffer a much more painful treatment for a serious dental disease (i.e., pure losses), or may enjoy smoking now but suffer long-term future health complications (i.e., sooner-gain and later-loss), or may take preventive measures now to obtain good health in the future (i.e., sooner-loss and later-gain). Several studies have examined pure losses tasks, but the research on the other two mixed tasks is scarce.

A previous study (Ostaszewski, 2007) tested mixed tasks by constructing a financial yes-or-no tradeoff involving a combination of a gain and loss. Participants needed to decide whether to accept an offer that could be either an immediate gain to be followed by a later loss or an immediate loss to be followed by a later gain. The study found the hyperboloid discounting type in these two tasks. Although it did not compare the difference in the discount rates, the k values, which indicated the rate, showed a trend in which the discount rate of the sooner-gain and later-loss task was lower than that of the sooner-loss and later-gain task. Estle et al. (2019) examined the difference in discount rates between mixed (sooner-loss and later-gain) and pure gains tasks because they focused on the self-control issue, which likely follows a pattern of a sooner loss followed by a later gain. They found that, when the combination represented a net loss but not a net gain, the discount rate of the mixed task was less steep than that of the pure gains task. However, they did not compare the other tasks and paid more attention to incorporating self-control in the discounting framework.

It is certainly possible for different laboratory tasks to yield different discount rates and represent different real-world behaviors and consequences. However, few studies have attempted to compare the discount rates for such tasks or examine the links between

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discounting rates measured through these tasks and real-world behaviors and consequences. This study aimed to fill that gap.

1.1 Tasks and Discount Rates

The discounted utility model, which is the normative model of intertemporal choice, assumes that individuals discount future outcomes with a constant ratio (discount rate). According to this model, an individual's discount rate should not change regardless of the method (e.g., choosing or matching) used to yield the discount rates and the sign of the outcomes (positive or negative). However, most of the evidence demonstrates that the choosing and matching methods yield inconsistent discount rates (Hardisty, Thompson, et al., 2013; Cohen et al., 2020). Specifically, a lower discount rate is found via matching methods than via choosing methods (Read & Roelofsma, 2003; Freeman et al., 2016). Furthermore, discount rates from monetary gains are higher than those from losses (Thaler, 1981), known as "gain-loss asymmetry" or the "sign effect." These findings and others suggest that no one constant discount rate can describe results for any individual. Individuals may have different discount rates in mixed and pure tasks.

1.2 Discount Rates in the Lab and Real-world Behaviors and Consequences

The correlations between discounting rates and real-world behaviors and consequence have been widely studied (Urminsky & Zauberman, 2015). The research has found higher discount rates than matched ones among addicted people, such as those addicted to food (Mole et al., 2015), cigarettes (Reynolds & Fields, 2012), and videogames (Irvine et al., 2013). In addition, a meta-analysis of discounting and addictive behavior (Mackillop et al., 2011) showed that monetary discount rates are higher among individuals who are dependent on alcohol (Cohen's $d = 0.50$), tobacco ($d = 0.57$), opiates ($d = 0.76$), stimulants ($d = 0.87$), and gambling ($d = 0.79$) than among non-dependent controls. Another meta-analysis (Amlung et al., 2017) revealed that discounting is robustly associated with continuous measures of addiction, specifically regarding severity and quantity frequency of alcohol (Pearson's $r = 0.14$), tobacco ($r = 0.17$), gambling ($r = 0.16$), and cannabis ($r = 0.10$).

Researchers have also tried to use discounting to explain short-sighted real-world behaviors in the normal population, such as consumer and health decisions. However, a great deal of the research on the relations between discount rates and field behaviors (e.g., exercise, seatbelt using, and risky sexual activity) has revealed only weak correlations (Daugherty & Brase, 2010; Sanchez-Roige et al., 2018). For example, Chabris et al. (2008) examined the relations between discount rates and field behaviors and consequences (e.g., BMI, smoking, and heathy food eating) and found them to be small: None exceeded 0.28, and many were close to 0. However, they found that the discount rate had at least as much predictive power as other variables (e.g., gender, age, education) in their dataset, which suggests that the discount rate can be a predictor of real-world behaviors and consequences. Moreover, the superiority of the discount rate over other predictors was enhanced when the behaviors and consequences were aggregated into an index. However, several other studies do not support the claim that discounting relates to potentially short-sighted real-world behaviors. For instance, there is no evidence to support the claim that higher discount rates via the choosing method correlate with more caffeine use (Sanchez-Roige et al., 2018) and younger age at first sex (Hardisty, Thompson, et al., 2013). Notably, most of these studies used pure gains tasks to generate discount rates and examine the relations between them and real-world behaviors and consequences. However, Hardisty, Thompson, et al. (2013) showed that discount rates from pure gains or losses tasks predicted different consequential outcomes. For example, discount rates via a pure losses task with an alternative titration method had a positive predictive relation regarding the frequency of dental checkups while those via a pure gains task with the same method did not.

We argue that the pure gains monetary tasks used in the laboratory do not provide a realistic representation of the important intertemporal behaviors and consequences with which people deal every day. We speculate that this may be part of the reason why discounting rates are only weakly related to real-world behaviors and consequences. Thus, we proceeded on the assumption that different tasks (i.e., pure gains, pure losses, sooner-gain and later-loss, sooner-loss and later-gain) are associated with field behaviors and consequences differentially based on the nature of the task.

We conducted two experiments to determine the differences in discount rates between the four tasks and examine whether the tasks could represent different real-world behaviors and consequences. In Experiment 1, we examined the difference in discount rates between the four tasks using a student sample with a well-validated and widely used monetary choice questionnaire (MCQ; Kirby et al., 1999; Kirby, 2009).[1] In Experiment 2, we examined the difference in discount rates by extending the sample from students to community individuals with the same questionnaire, and estimated the relations between the discount rates yielding from the four tasks and real-world behaviors and consequences.

2 Experiment 1: Comparing Mixed Gain-Loss Intertemporal Tradeoffs with Pure Ones

2.1 Method

In Experiment 1, 186 students from Zhejiang University of Technology were approached in the library and were presented with an invitation letter asking them to log on to a website for participation in our survey. They were told that, after the experiment, the website would randomly select 1 out of 10 participants, who would receive 30 Chinese yuan (CNY).

[1]The money amounts and delays in our study were the same as those used in the MCQ, except that we used the money symbol "¥" instead of "$."

Subsequently, they scanned a quick response (QR) code on the survey website and were randomly assigned to one of the four conditions: pure gains, pure losses, sooner-gain and later-loss, and sooner-loss and later-gain.[2]

Participants in each condition were presented with 27 items about which they needed to make choices. Those in the pure gains condition needed to choose between a smaller immediate gain and a larger delayed gain; those in the pure losses condition needed to choose between a smaller immediate loss and a larger, delayed loss; those in the sooner-gain and later-loss condition needed to decide whether to accept a smaller, immediate gain followed by a larger, delayed loss; those in the sooner-loss and later-gain condition needed to decide whether to accept a smaller, immediate loss followed by a larger, delayed gain. The item order, specific amounts, delays, and *k* values are shown in Table 1. Items are available in a supplement. Further details on the materials and data are available from https://osf.io/eq79p/. Examples are given below:

Pure gains task:

If you are faced with the following pairing options, which would you prefer:
A: receive 24 CNY now
B: receive 35 CNY in 29 days

Pure losses task:

If you are faced with the following pairing options, which would you prefer:
A: pay 24 CNY now
B: pay 35 CNY in 29 days

Sooner-gain and later-loss task:

Are you willing to "receive 24 CNY now and pay 35 CNY in 29 days"? Please choose the option to indicate your willingness.
A: Yes
B: No

[2]We ran a pretest study with tasks as a within-subject factor and with task order as a between-subject factor to detect whether there was an order effect in the tasks. One hundred and seven participants completed the four tasks sequentially (version 1): a choice of receiving 640 CNY today or receiving 780 CNY in 12 months (pure gains), a choice of paying 640 CNY today or paying 780 CNY in 12 months (pure losses), a choice of whether to accept an offer to receive 640 CNY today and pay 780 CNY in 12 months (sooner-gain and later-loss), and a choice of whether to accept an offer to pay 640 CNY today and receive 780 CNY in 12 months (sooner-loss and later-gain). One hundred and six participants completed the four tasks in a reversed order (version 2). The results showed that the proportion that chose the larger-later option in the pure gains and pure losses tasks were 25.2% and 50.5%, respectively, in version 1 and 54.7% and 31.1% in version 2. The proportion that chose the YES option in the sooner-gain and later-loss task and sooner-loss and later-gain task were 43.0% and 66.4% in version 1 and 24.5% and 65.1% in version 2. There was an order effect in the tasks. Therefore, if we used a within-subjects design in the formal study, it would have to been 24 task order conditions to detect the order effect, which is too many, and the participants would have needed to answer 108 items, which is also too many. Thus, we decided to use a between-subjects design.

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Sooner-loss and later-gain task: Are you willing to "pay 24 CNY now and receive 35 CNY in 29 days"? Please choose the option to indicate your willingness.

A: Yes
B: No

Table 1: Twenty-seven items ordered by *k* value: amounts and delays.

Item	SIA	LDA	Delay (days)	*k* value	LDA size
13	34	35	186	0.00016	Small
1	54	55	117	0.00016	Medium
9	78	80	162	0.00016	Large
20	28	30	179	0.0004	Small
6	47	50	160	0.0004	Medium
17	80	85	157	0.0004	Large
26	22	25	136	0.001	Small
24	54	60	111	0.001	Medium
12	67	75	119	0.001	Large
22	25	30	80	0.0025	Small
16	49	60	89	0.0025	Medium
15	69	85	91	0.0025	Large
3	19	25	53	0.006	Small
10	40	55	62	0.006	Medium
2	55	75	61	0.006	Large
18	24	35	29	0.016	Small
21	34	50	30	0.016	Medium
25	54	80	30	0.016	Large
5	14	25	19	0.041	Small
14	27	50	21	0.041	Medium
23	41	75	20	0.041	Large
7	15	35	13	0.1	Small
8	25	60	14	0.1	Medium
19	33	80	14	0.1	Large
11	11	30	7	0.25	Small
27	20	55	7	0.25	Medium
4	31	85	7	0.25	Large

The monetary choice questionnaire assesses discounting preferences across three delayed magnitudes (LDA size): small (25–35), medium (50–60), and large (75–85). SIA = smaller immediate amount; LDA = larger delayed amount; k value is the value of the discount rate determined by SIA = LDA /(1+k*Delay) (Mazur, 1987).[3]

2.2 Results and Discussion

A freely available Excel-based program was used to calculate the k values. Following the literature, the k values were normalized using log transformation because raw k values tend to be skewed (Kaplan et al., 2016).

We excluded one participant each in the pure gains, pure losses, and sooner-gain and later-loss conditions as well as two participants in the sooner-gain and later-loss condition because they showed an overall consistency score lower than 75% (see Kaplan et al., 2016), leaving a total sample of 181 participants (90 males, M_{age} = 22.30, SD = 3.54) for the final analysis (see Table 2).

Table 2: Demographic characteristics and k value of the samples.

Tasks:	Pure gains	Pure losses	Sooner-gain later-loss	Sooner-loss later-gain
N	46	45	46	44
Male	20 (43.5%)	28 (62.2%)	21 (45.7%)	21 (47.7%)
Age (*SD*)	21.98 (2.30)	22.71 (2.51)	21.74 (2.26)	22.80 (5.86)
k value (*SD*)	0.0486 (0.0587)	0.0052 (0.0072)	0.0020 (0.0046)	0.0244 (0.0282)
Log *k* value (*SD*)	−1.68 (0.69)	−2.82 (0.78)	−3.28 (0.63)	−2.08 (0.85)

Using ANOVA, we found a statistically significant difference in mean log k value of the four tasks (F (3,177) = 43.46, p < .001, η^2 = 0.424). Post-hoc tests revealed that the mean log k value of the sooner-gain and later-loss task was lower than that of the pure losses task (p = .019, d = −0.65), the mean log k value of the pure losses task was lower than that of the sooner-loss and later-gain tasks (p < .001, d = 0.91), and the mean log k value of the sooner-loss and later-gain task was lower than that of the pure gains task (p = .050, d = −0.52). Therefore, the order of these tasks according to their mean log k value, from highest to lowest, was as follows: pure gains, sooner-loss and later-gain, pure losses, and

[3]We used Mazur's hyperbolic model to yield the discount rates because, although several models have been developed to describe intertemporal choice (e.g., Loewenstein & Prelec, 1993; Myerson et al., 2001), the hyperbolical function devised by Mazur (1987) is the one most typically used by researchers (Franco-Watkins et al., 2016). Kirby used Mazur's model to fit data produced from his 27-item questionnaire. Franco-Watkins et al. used Mazur's model to fit data from intertemporal choice with both pure gains and also pure losses. Because our four tasks were adopted or adapted from Kirby's questionnaire, we used Mazur's model.

sooner-gain and later-loss. (See Figure 1 for the distribution of log k values of the four tasks). This result is consistent with those on gain-loss asymmetry (Thaler, 1981) and the trend of discount rates in the two mixed tasks shown by Ostaszewski (2007).

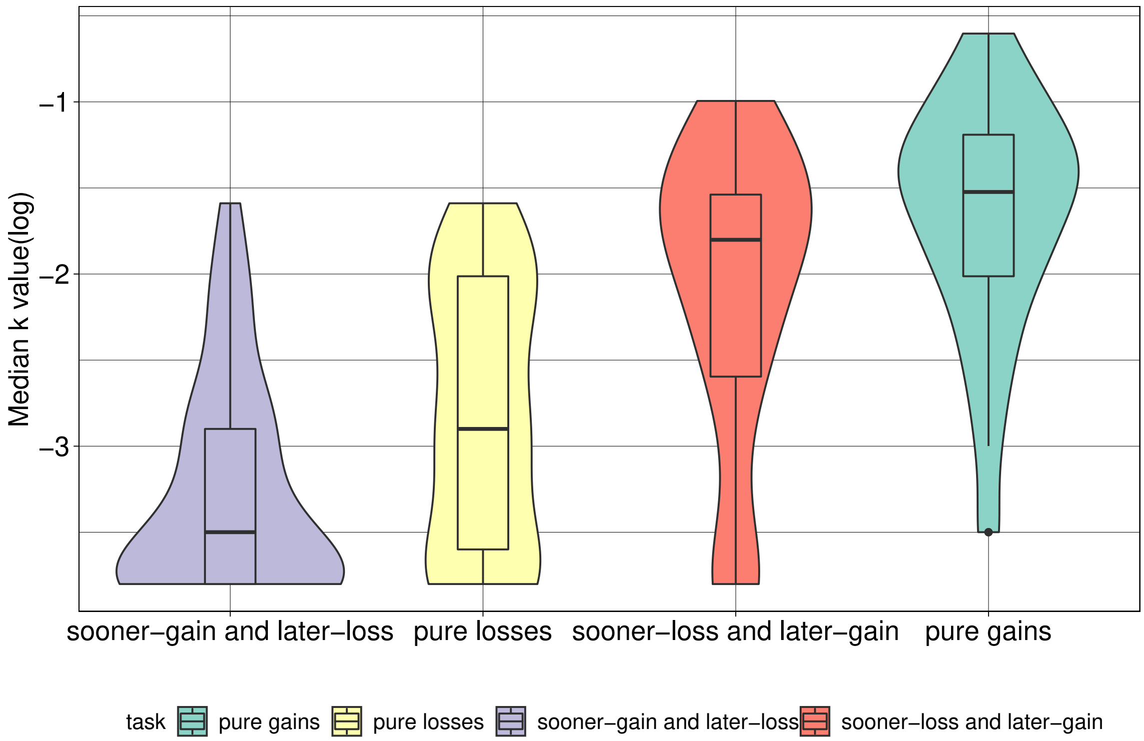

FIGURE 1: Violin and box plots of the median k value (log) for the four discounting tasks, sorted according to the magnitude of the median k value (log). The crossbar of each box represents the median; the bottom and top edges of the box represent the first and third quartiles; the dot represents one data point, which is an extreme outlier. One data point lies outside the range of this figure in the pure gains condition. The violin-shaded areas reflect the distribution shape of the data.

TABLE 3: The effect of possible mechanisms on the discounting rate of four tasks.

Tasks:	Pure gains	Sooner-loss later-gain	Pure losses	Sooner-gain later-loss
Present bias	↑	-	↓	-
Status quo effect	-	↑	-	↓
Sequence effect	-	↓	-	↓
Salience account	-	↓	-	↓
Loss aversion	-	↑	-	↓
Debt aversion	-	↑	↓	↓

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As shown in Table 3, we concluded that various effects could contribute to the differences in the discounting rates between the four tasks. The "↑" represents an effect that can help to increase the discount rate in a task, "↓" represents an effect that can help to decrease the discount rate in a task, and "-" represents an effect that does not exist in a task.

Present bias describes a condition in which people are willing to experience the outcome now rather than in the future regardless of whether it is positive or negative (Hardisty, Appelt, et al., 2013), which could help to yield a higher discount rate in the pure gains task and a lower discount rate in the pure losses task.

The status-quo effect indicates a preference for the current state of affairs or a tendency to leave a situation unchanged (Lempert & Phelps, 2016; Patty, 2006), which could lead to more rejections in the mixed tasks, in which participants were asked to keep a status-quo or choose a prospect. This effect could help to yield the higher discount rate in the sooner-loss and later-gain task and the lower discount rate in the sooner-gain and later-loss task.

The sequence effect proposed by Loewenstein and Prelec (1993) posits that people favor an increasing sequence and disfavor a decreasing sequence. In our study, the sooner-gain and later-loss task could be identified as a decreasing sequence, while the sooner-loss and later-gain task may be an increasing sequence; the sequence effect could help to yield the lower discount rate of the sooner-gain and later-loss task and the higher discount rate of the sooner-loss and later-gain task.

The salience account suggests that a discounting rate of intertemporal sequences is generally (though not always) smaller than that of a single-dated outcome (Jiang et al., 2014). When choosing between two single-dated outcomes, people trade off outcomes against delays, and they may pay equal attention to these two attributes (delay and outcome). However, when choosing between prospects involving sequences, people may be more focused on outcomes than on delays because, in sequences, outcomes are more salient than delays. Thus, choices involving sequences often show lower discounting rates than choices between single-dated outcomes (Jiang et al., 2017; Jiang et al., 2016; Jiang et al., 2014; Sun & Jiang, 2015). In the mixed tasks, prospects can be seen as sequences. Therefore, the salience account would predict lower discounting rates for the mixed tasks than for the other two tasks.

Loss aversion refers to the tendency to prefer avoiding losses to acquiring equivalent gains, which is identified in risky choice rather than intertemporal choice. Some researchers have borrowed this definition to construct models of intertemporal choice (Loewenstein & Prelec, 1992; Scholten & Read, 2010). Loss aversion would predict more rejections in the mixed tasks, which would help to yield the lower discount rate in the sooner-gain and later-loss task and the higher discount rate in the sooner-loss and later-gain task. However, whether loss aversion actually exists is debatable. Some researchers hold that the current evidence does not support the view that losses tend to be any more impactful than gains (Gal & Rucker, 2018).

Debt aversion suggests that people are unwilling to enter into a financial contract framed or labeled as “debt” (Caetano et al., 2019). This aversion has been used to explain why people often pay off mortgages and student loans quicker than they have to (Eckel et al., 2007; Loewenstein & Thaler, 1989). In the mixed and pure losses tasks, the option involves a loss if it is framed as a debt by participants, which could motivate them to avoid a loss or pay it off as soon as possible. Therefore, debt aversion could help to yield the lower discount rates in the pure losses task and sooner-gain and later-loss task and the higher discount rate in the sooner-loss and later-gain task.

Ultimately, a discount rate is an end product of mechanisms involving many psychological factors, which affect the participants involved in different tasks in various ways. The underlying mechanism of the differences in discount rates between the four tasks remains an interesting topic for exploration.

3 Experiment 2: Estimating the Relations between Discount Rates and Real-world Behaviors and Consequences

Experiment 1 revealed the differences in discount rates between the four tasks preliminarily. To make the results more robust, we extended the sample from students to community individuals in Experiment 2. Furthermore, we estimated the relations between the four tasks and real-world behaviors and consequences.

We assumed that any task at least measures some kind of discounting rate. Thus, we predicted that, for all four tasks, a higher discounting rate was associated with a lower frequency of floss use, less exercise, larger BMI, a lack of following a diet, less credit paid in full, a higher frequency of smoking, a higher frequency of alcohol use, a higher frequency of gambling, a higher frequency of junk food eating, more time used for entertainment and social interaction with smartphones, less savings compared to colleagues, less savings compared to contemporaries, less success compared to colleagues, and less success compared to contemporaries, largely based on the literature (Amlung et al., 2017; Chabris et al., 2008; Hardisty, Thompson, et al., 2013; Mackillop et al., 2011). (See the supplement for the item wording; the full materials and data are available at https://osf.io/eq79p/.)

Moreover, we predicted that the discounting rates yielded from the tasks that represented real-world behaviors and consequences most closely would be the best predictors of those behaviors and consequences. Specifically, we predicted that the pure gains task would do better for saving behavior; the pure losses task would do better for credit paid in full; that smoking, alcohol use, gambling, junk food eating, and smartphone use for entertainment would be explained better by the sooner-gain and later-loss task; and that exercise, floss use, and diet status would be explained better by the sooner-loss and later-gain task. We made no predictions about which tasks would be most closely related to BMI and success because there are too many influencing factors for them.

3.1 Method

Eight hundred and sixty-nine participants were recruited from Sojump (http://www.sojump.com), a popular online survey website in China. After completing discounting tasks similar to those used in Experiment 1, participants were asked to report some of their personal behaviors and consequences (mostly taken from Chabris et al. [2008]; listed in Table 5). The order of the two options in the discounting task items was counterbalanced among participants.

3.2 Results and Discussion

As in Experiment 1, we used an Excel-based program to calculate the discounting rates. Six participants in the pure gains, 17 participants in the pure losses, 16 participants in the sooner-loss and later-gain, and 15 participants in the sooner-gain and later-loss conditions who showed an overall consistency score lower than 75% were excluded. We found no difference in the exclusion amounts of the four tasks (χ^2(3, N = 869) = 5.9, p = .116). Hence, they were excluded safely, leaving 815 valid questionnaires[4] (316 males, M_{age} = 30.37, SD = 8.18) for the final analysis (see Table 4).

Table 4: Demographic characteristics and k values of the samples.

Tasks:	Pure gains	Pure losses	Sooner-gain later-loss	Sooner-loss later-gain
N	209	204	197	205
Male	76 (33.4%)	76 (37.3%)	81 (41.1%)	82 (40.0%)
Age (SD)	30.26 (7.80)	30.59 (8.06)	30.53 (8.16)	30.17 (8.68)
k value (SD)	0.0423 (0.0613)	0.0156 (0.0471)	0.0129 (0.0492)	0.0250 (0.0501)
Log k value (SD)	−1.84 (0.73)	−2.74 (0.86)	−3.00 (0.83)	−2.21 (0.78)

3.2.1 Tasks and Discount Rates

The differences in discount rates between the four tasks are consistent with those in Experiment 1. The four tasks yielded different discount rates (F (3,811) = 86.88, p < .001, η^2 =

[4]Among the 815 participants, 122 (15.0%) were full-time students; 44 (5.4%) were production staff; 55 (6.7%) were salespeople; 23 (2.8%) were marketing or PR staff; 14 (1.7%) were customer service staff; 73 (9.0%) were administrative or support service staff; 29 (3.6%) were human resources staff; 40 (4.9%) were finance staff or auditors; 81 (9.9%) were officers or clerks; 95 (11.7%) were technical or R&D staff; 135 (16.6%) were management staff; 40 (4.9%) were teachers; 3 (0.4%) were consultants; 45 (5.5%) were professionals (e.g., accountants, lawyers, architects, medical staff, journalists); and 16 (2.0%) were others.

0.243), and post-hoc tests revealed the same order of discount rates among the four tasks as that found in Experiment 1 (*p*s < .005).[5]

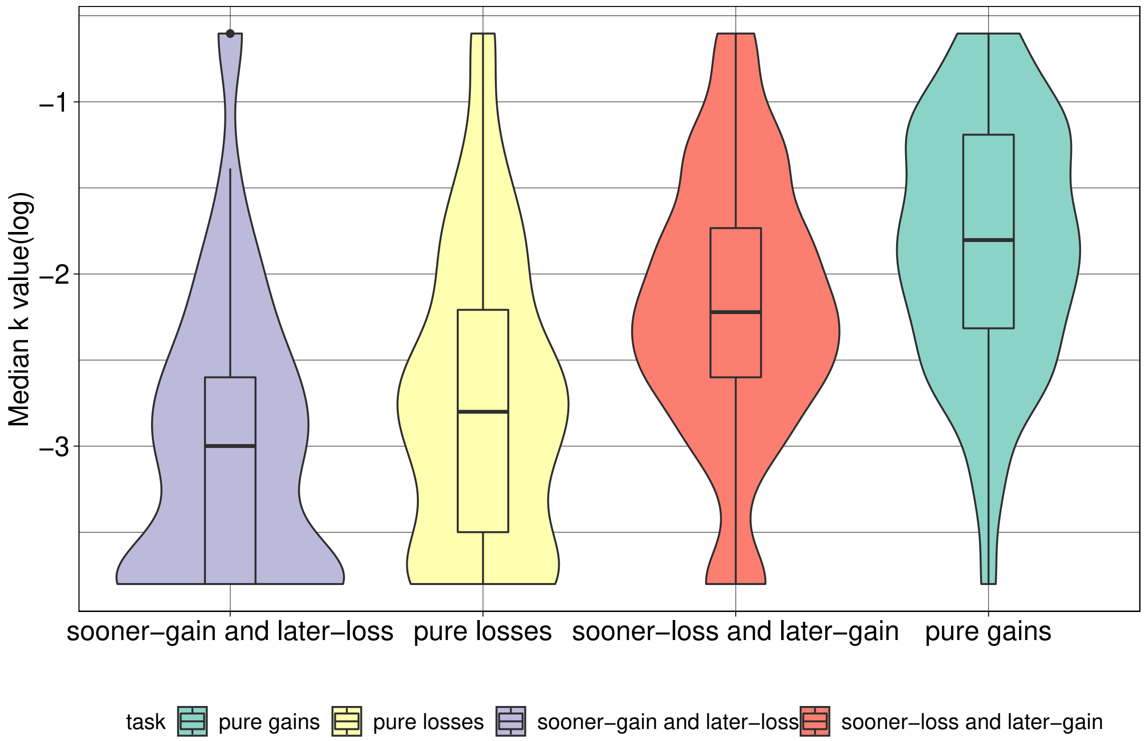

FIGURE 2: Violin and box plots of the median *k* value (log) for the four discounting tasks, sorted according to the magnitude of the median *k* value (log). The crossbar of each box represents the median; the bottom and top edges of the box represent the first and third quartiles. One data point lies outside the range of this figure in the sooner-gain and later-loss condition. The violin-shaded areas reflect the distribution shape of the data.

3.2.2 Discount Rates and Real-world Behaviors and Consequences

We reverse-scored several items to make positive values, indicating the relations in the predictive direction we assumed.[6] We ran the liner regressions, and reported the results in Table 5. The columns show the estimates of the log *k* values when the behaviors

[5]To examine whether the sample source (students in Experiment 1 vs. community individuals in Experiment 2) had an effect on the discount rates, we conducted a two-way ANOVAs with the sample source as one factor and the task as another. There was a main effect of task (F (3, 988) = 57.81, $p < .001$, $\eta^2 = 0.218$), but there was no main effect of the sample source and no interaction between the task and sample source (*p*s > .05). Thus, we concluded there was no significant difference between the two samples.

[6]Specifically, the higher scores on behaviors and consequences in Table 5 indicate larger BMI; less exercise; lower frequency of floss use; less credit paid in full; higher frequency of smoking; higher frequency of alcohol use; higher frequency of gambling; higher frequency of junk food eating; more time used for entertainment and social interaction with smartphones; less saving compared to colleagues; less savings compared to contemporaries; less success compared to colleagues; and less success compared to contemporaries. Diet status = 0 if participants are on a diet and = 1 if participants are not.

and consequences are regressed on the demographic characteristics (i.e., age, age^2/100, education, gender and family income) and the log k value. The complete regression results are provided at the end of this paper (in the Extended Tables). The results revealed that the discounting rates from the four tasks cannot explain the behaviors and consequences except for a few, even some in the reverse-predictive direction, which remains to be studied. Ultimately, we found that the evidence supporting a relation between the discount rates of the four tasks and the different real-world behaviors and consequences was insufficient.

Table 5: Regressions estimates of discount rates yielded from four tasks.

Tasks:	Pure gains	Pure losses	Sooner-gain later-loss	Sooner-loss later-gain
BMI	0.15	0.07	−0.14	−0.01
Exercise§	0.06	−0.07	−0.06	−0.31**
Diet status§	0.04	0.06	−0.13**	0.13**
Floss using§	−0.10	0.15	−0.27**	0.02
Credit paid in full§£	0.17	0.03	0.21*	−0.22*
Smoking	0.08	−0.07	0.10	0.15
Alcohol using	0.14	0.04	0.11	0.02
Gambling	0.07	−0.09	0.30***	−0.04
Junk food eating	−0.02	−0.05	0.04	0.08
Smartphone using	−0.01	−0.09	−0.04	0.07
Save / colleague§	0.11	0.00	−0.10	−0.06
Save / contemporary§	0.09	0.08	−0.11	−0.09
Success / colleague§	0.05	0.01	−0.08	−0.17
Success / contemporary§	0.16	0.01	−0.10	−0.10

§ These items were reverse-scored so that positive values indicated a correlation in the predicted direction; £ excluded participants who did not use any credit tools because we could not arbitrarily classify them as preferring the present or the future; hence, the samples of the items of the four tasks are 166, 159, 157, and 163, respectively; * $p < .05$; ** $p < .01$; *** $p < .001$.

3.2.3 Pure Gains Task and Real-world Behaviors and Consequences

The evidence from research on the relations between intertemporal choices of pure gains task in the laboratory and real-world behaviors and consequences is relatively sufficient; thus, this issue will be discussed first. In our study, the effects of the discount rate yielded from pure gains task are statistically insignificant for all behaviors and consequences. Previous studies based on non-clinical participants have shown that discount rates are weakly correlated with real-world behaviors and consequences (Chabris et al., 2008; Daugherty & Brase, 2010; Sanchez-Roige et al., 2018). For example, Chabris et al. (2008) conducted three studies to examine the relations between discount rates and behaviors. Their Study 3, which measured 14 behaviors and consequences in normal individuals with online questionnaires, is similar to the pure gains condition in our Experiment 2. The results of their Study 3 showed that the discounting rate had a positive and significant correlation with BMI and credit card bill paid in full but a negative and significant relationship with prescription drug compliance. Our results are not consistent with these. The main reasons for the difference between the results may be that their study excluded participants who always chose either the delayed or immediate rewards and used a larger sample size than that used in our pure gains condition; moreover, the participants in their study were incentivized to be incentive compatible. These different measures may have led to the different results. Although the effects of the discount rates on all the behaviors and consequences we measured did not reach statistical significance, most of them were consistent with the expected directions (only three of the 14 were in the opposite direction). Therefore, our study is generally consistent with previous studies on the relations between the discount rate of the pure gains task and real-world behaviors and consequences.

Some scholars have discussed why the discount rate is weakly related to real-world behaviors and consequences (Urminsky & Zauberman, 2015). For example, regarding the complexity of individual behavior, some behaviors, which are assumed to be intertemporal choices, may not be dominated or even affected by discount rates. For instance, some people exercise because the people around them do (like in the herd effect). Once these social influences exist, people's decision making does not depend on their own independent deliberations, and the impact of the discount rate on real-world outcomes become smaller or even disappears. Furthermore, the behaviors and consequences considered by researchers to be discount types are actually not related or are the opposite. For example, some people always need to balance between working hard for money and exercising, but it is unreasonable to describe sacrificing exercise in order to work as short-sighted. After all, making money is also done to obtain a better life and prepare for the future.

3.2.4 Other Tasks and Real-world Behaviors and Consequences

As Table 5 shows, we found in the pure losses task that the discount rate could not explain any real-world behavior and consequence, which is inconsistent with Hardisty, Thompson, et al. (2013). Hardisty, Thompson, et al. (2013) found that the discount rates yielded from pure losses task with an alternative titration method could predict some consequential outcomes (e.g., exercise, credit paid in full). Our results and Hardisty, Thompson, et al.'s may differ because their study used non-parametric correlations, while we used regressions and controlled for other variables; moreover, we used Kirby's task to yield the discount rate while they used a self-designed task. For the newly introduced tasks, the findings are both expected and unexpected. In the sooner-gain and later-loss task, the discount rate can explain gambling (b = 0.30, p = .001) and credit paid in full (b = 0.21, p = .024), consistent with our prediction; however, its effects on diet status (b = −0.13, p = .002) and floss use (b = −0.27, p = .002) are significant but contrary to our prediction. In the sooner-loss and later-gain task, the discount rate can explain diet status (b = 0.13, p = .002), consistent with our prediction; however, its effects on credit paid in full (b = −0.22, p = .031) and exercise (b = −0.31, p = .006) are significant but contrary to our prediction. In these three tasks, the other relations are not statistically significant, and a considerable part of the behaviors and consequences (five, nine, and eight of the 14 outcomes in the pure losses, sooner-gain and later-loss, and sooner-loss and later-gain tasks) are contrary to our expectations.

It is possible that the discount rate of a pure gains task can represent a "universal" discount rate, which is related to real behaviors and consequences, while other tasks cannot. The relations in the two mixed tasks may be false correlations (false positive errors) caused by multiple tests. However, other discount tasks may also predict behaviors and consequences, but our tasks did not include zero or negative discount rate situations because we used and adjusted Kirby's discounting task (Kirby et al., 1999; Kirby, 2009). Previous research has shown that loss outcomes can yield a negative discount rate (Hardisty, Thompson, et al., 2013). The results may be different if the tasks can accommodate zero or negative discount rates.

4 General Discussion

In Experiment 1, we compared mixed gain-loss intertemporal choices with pure gains or pure losses choices with a college student sample. The results demonstrated that the discount rate ordering of the four tasks, from highest to lowest, was pure gains, sooner-loss and later-gain, pure losses, and sooner-gain and later-loss. In Experiment 2, we repeated the process for the four tasks with community participants and also measured their self-reported real-world behaviors and consequences. We found that the evidence supporting the claim that discount rates from different tasks are related to different real-world behaviors and consequences was insufficient.

In both experiments, we used hypothetical tasks rather than real monetary incentives to yield the discount rates because it is almost impossible for us to ask participants to pay money in the pure losses and mixed tasks. Fortunately, previous studies have shown that there are no differences between real and hypothetical intertemporal outcomes at the behavioral level (Johnson & Bickel, 2002; Madden et al., 2003) or neural level (Bickel et al., 2007).

We have confidence in our finding that different tasks yield different discount rates. The results of this study further the research on gain-loss asymmetry. However, more research is needed to explore the relations between the discount rates of different tasks and real-world behaviors and consequences.

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Appendix

Extended Table 1. Real-world behaviors and consequences regression in pure gains task (s.e. in parentheses).

Predictor	BMI	Exercise§	Diet§	Floss§	Credit§£	Smoke	Alcohol	Gamble	Junk food	Phone	Save.1§	Save.2§	Suc.1§	Suc.2§
Log k	0.15	0.06	0.04	−0.10	0.08	0.17	0.14	0.07	−0.02	−0.01	0.11	0.09	0.05	0.16
	(0.08)	(0.09)	(0.05)	(0.09)	(0.07)	(0.11)	(0.09)	(0.10)	(0.10)	(0.09)	(0.10)	(0.09)	(0.09)	(0.09)
Age	0.91**	−0.49	−0.18	−0.80*	−0.64*	0.81	0.49	0.56	−0.76	−1.14**	−0.43	−0.06	0.43	0.32
	(0.34)	(0.40)	(0.20)	(0.41)	(0.31)	(0.63)	(0.38)	(0.41)	(0.43)	(0.39)	(0.42)	(0.40)	(0.39)	(0.39)
$Age^2/100$	−0.69*	0.56	0.18	0.82*	0.87**	−0.96	−0.31	−0.56	0.65	0.92*	0.57	0.08	−0.51	−0.41
	(0.35)	(0.41)	(0.20)	(0.42)	(0.32)	(0.68)	(0.39)	(0.43)	(0.44)	(0.40)	(0.43)	(0.41)	(0.40)	(0.40)
Education	−0.03	0.01	0.00	0.01	−0.02	−0.15	0.02	−0.08	0.08	0.07	−0.05	−0.16*	−0.28***	−0.25**
	(0.06)	(0.08)	(0.04)	(0.08)	(0.06)	(0.09)	(0.07)	(0.08)	(0.08)	(0.07)	(0.08)	(0.08)	(0.07)	(0.07)
Gender(male)	0.65***	−0.25	−0.06	0.04	0.44***	−0.18	0.59***	0.30*	−0.26	−0.08	−0.10	0.01	0.08	0.02
	(0.12)	(0.14)	(0.07)	(0.15)	(0.11)	(0.17)	(0.14)	(0.15)	(0.16)	(0.14)	(0.15)	(0.14)	(0.14)	(0.14)
Family income	−0.11	−0.14	−0.06	−0.20**	0.10	−0.02	0.09	−0.01	0.17*	0.03	−0.19*	−0.24**	−0.36***	−0.40***
	(0.06)	(0.07)	(0.04)	(0.07)	(0.06)	(0.09)	(0.07)	(0.07)	(0.08)	(0.07)	(0.08)	(0.07)	(0.07)	(0.07)
Observations	209	209	209	209	166	209	209	209	209	209	209	209	209	209
R^2	0.243	0.050	0.034	0.070	0.056	0.202	0.170	0.032	0.062	0.096	0.070	0.093	0.201	0.222

Extended Table 2. Real-world behaviors and consequences regression in pure losses task (s.e. in parentheses).

Predictor	BMI	Exercise§	Diet§	Floss§	Credit§£	Smoke	Alcohol	Gamble	Junk food	Phone	Save.1§	Save.2§	Suc.1§	Suc.2§
Log k	0.07	−0.07	0.06	0.15	0.03	−0.07	0.04	−0.09	−0.05	−0.09	0.00	0.08	0.01	0.01
	(0.07)	(0.07)	(0.04)	(0.08)	(0.11)	(0.08)	(0.08)	(0.09)	(0.08)	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)
Age	−0.08	−0.16	−0.22	−0.04	0.94	0.17	0.38	0.51	−0.84*	−0.74	−0.14	−0.11	0.16	0.51
	(0.30)	(0.30)	(0.18)	(0.36)	(0.72)	(0.35)	(0.38)	(0.40)	(0.34)	(0.40)	(0.35)	(0.37)	(0.37)	(0.35)
$Age^2/100$	0.27	0.11	0.18	−0.09	−1.08	−0.09	−0.32	−0.48	0.56	0.63	0.11	0.15	−0.24	−0.51
	(0.29)	(0.30)	(0.18)	(0.35)	(0.74)	(0.34)	(0.37)	(0.39)	(0.33)	(0.39)	(0.35)	(0.36)	(0.36)	(0.34)
Education	0.02	0.00	0.03	−0.13	−0.07	−0.05	−0.02	−0.08	−0.01	−0.05	0.11	0.09	0.01	−0.04
	(0.06)	(0.06)	(0.03)	(0.07)	(0.11)	(0.07)	(0.07)	(0.08)	(0.07)	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)
Gender(male)	0.46***	−0.22	−0.12	−0.03	0.25	0.83***	0.55***	0.48**	−0.08	−0.16	−0.16	−0.33*	−0.28	−0.26
	(0.12)	(0.12)	(0.07)	(0.14)	(0.17)	(0.14)	(0.15)	(0.15)	(0.13)	(0.15)	(0.14)	(0.14)	(0.14)	(0.13)
Family income	−0.08	−0.15*	−0.09*	−0.21**	−0.08	−0.04	0.13	0.02	0.05	0.02	−0.41***	−0.36***	−0.29***	−0.37***
	(0.06)	(0.06)	(0.04)	(0.07)	(0.11)	(0.07)	(0.08)	(0.08)	(0.07)	(0.08)	(0.07)	(0.08)	(0.07)	(0.07)
Observations	204	204	204	204	159	204	204	204	204	204	204	204	204	204
R^2	0.154	0.082	0.082	0.115	0.036	0.176	0.111	0.062	0.116	0.050	0.170	0.134	0.110	0.163

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Extended Table 3. Real-world behaviors and consequences regression in sooner-gain and later-loss task (s.e. in parentheses).

Predictor	BMI	Exercise§	Diet§	Floss§	Credit§£	Smoke	Alcohol	Gamble	Junk food	Phone	Save.1§	Save.2§	Suc.1§	Suc.2§
Log k	−0.14	−0.06	−0.13**	−0.27**	0.21*	0.10	0.11	0.30***	0.04	−0.04	−0.10	−0.11	−0.08	−0.10
	(0.10)	(0.08)	(0.04)	(0.09)	(0.09)	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)
Age	0.76	−0.19	−0.08	−0.77	0.01	1.00*	0.61	1.14**	−0.42	0.57	0.18	0.57	0.61	0.56
	(0.45)	(0.38)	(0.19)	(0.40)	(0.50)	(0.39)	(0.37)	(0.42)	(0.42)	(0.42)	(0.37)	(0.37)	(0.39)	(0.38)
$Age^2/100$	−0.53	0.13	0.13	0.80*	−0.21	−0.92*	−0.57	−1.13**	0.25	−0.64	−0.09	−0.47	−0.56	−0.52
	(0.45)	(0.39)	(0.19)	(0.40)	(0.50)	(0.39)	(0.37)	(0.42)	(0.43)	(0.42)	(0.37)	(0.37)	(0.39)	(0.38)
Education	−0.08	0.03	−0.04	−0.07	−0.17	−0.14*	0.12	−0.04	−0.02	0.10	−0.05	−0.10	−0.11	0.01
	(0.08)	(0.07)	(0.03)	(0.07)	(0.09)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.07)	(0.07)
Gender(male)	0.52**	−0.05	0.05	0.20	−0.11	1.18***	0.59***	0.22	−0.31	−0.06	−0.06	−0.22	−0.15	−0.06
	(0.17)	(0.14)	(0.07)	(0.15)	(0.16)	(0.14)	(0.14)	(0.15)	(0.16)	(0.16)	(0.14)	(0.14)	(0.14)	(0.14)
Family income	−0.15	−0.12	−0.02	−0.06	−0.01	0.02	0.15*	0.00	−0.01	−0.10	−0.15*	−0.22**	−0.26***	−0.27***
	(0.08)	(0.07)	(0.03)	(0.07)	(0.08)	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)
Observations	197	197	197	197	157	197	197	197	197	197	197	197	197	197
R^2	0.134	0.031	0.083	0.097	0.096	0.337	0.186	0.118	0.060	0.037	0.046	0.098	0.099	0.085

Extended Table 4. Real-world behaviors and consequences regression in sooner-loss and later-gain task (s.e. in parentheses).

Predictor	BMI	Exercise§	Diet§	Floss§	Credit§£	Smoke	Alcohol	Gamble	Junk food	Phone	Save.1§	Save.2§	Suc.1§	Suc.2§
Log k	−0.01	−0.31**	0.13**	0.02	−0.22*	0.15	0.02	−0.04	0.08	0.07	−0.06	−0.09	−0.17	−0.10
	(0.09)	(0.11)	(0.04)	(0.09)	(0.10)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)	(0.09)
Age	0.22	−0.51	0.05	−0.67	−0.69	0.38	0.98**	0.27	−0.54	−0.39	−0.31	−0.18	−0.21	0.51
	(0.36)	(0.43)	(0.16)	(0.36)	(0.57)	(0.31)	(0.33)	(0.31)	(0.33)	(0.33)	(0.35)	(0.37)	(0.34)	(0.35)
$Age^2/100$	−0.13	0.33	−0.07	0.63	0.72	−0.31	−0.86**	−0.25	0.28	0.18	0.10	0.07	0.17	−0.57
	(0.35)	(0.42)	(0.16)	(0.35)	(0.60)	(0.30)	(0.32)	(0.30)	(0.32)	(0.32)	(0.35)	(0.36)	(0.33)	(0.34)
Education	−0.01	−0.09	0.01	−0.08	−0.20	0.04	0.09	0.00	0.05	0.14	−0.18*	−0.10	−0.12	−0.11
	(0.08)	(0.10)	(0.04)	(0.08)	(0.10)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)
Gender(male)	0.73***	0.22	0.03	0.03	−0.15	0.95***	0.63***	0.37**	−0.04	0.08	0.14	0.06	0.15	0.07
	(0.15)	(0.18)	(0.07)	(0.15)	(0.16)	(0.13)	(0.14)	(0.13)	(0.14)	(0.14)	(0.15)	(0.15)	(0.14)	(0.14)
Family income	0.04	0.07	−0.05	−0.06	−0.05	0.13	0.05	0.11	0.04	−0.15*	−0.22**	−0.21**	−0.20**	−0.26**
	(0.08)	(0.10)	(0.04)	(0.08)	(0.09)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)
Observations	205	205	205	205	163	205	205	205	205	205	205	205	205	205
R^2	0.147	0.057	0.078	0.047	0.076	0.282	0.187	0.074	0.104	0.119	0.143	0.081	0.101	0.085

Notes for Extended Table 1-4: § and £ have the same meanings as those given in Table 5 in the paper; * $p < .05$; ** $p < .01$; *** $p < .001$

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